

APPENDIX 1: Seth's letter on statutory requirements for NCA5

APPENDIX 2: Analysis of 141 U.S. Longterm Daily Precipitation Records.

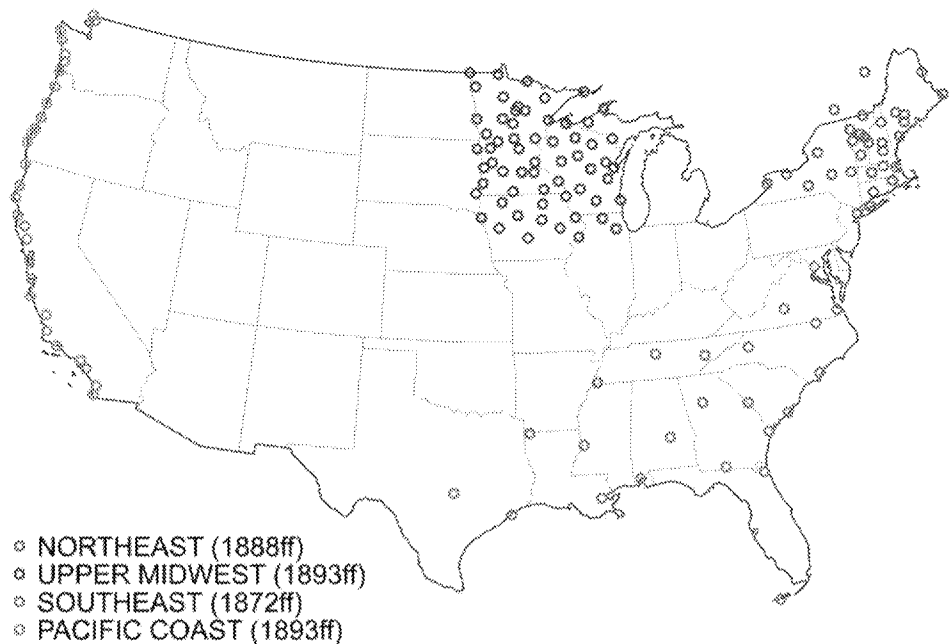


Figure. Stations used in the following analyses.

Table codes: (-) neg insignificant, -- neg significant, (+) pos insignificant, ++ pos significant.

Column 1: Measure
Column 2: Number of stations in that region
Column 3: Count of stations exhibiting a significant positive trend
Column 3: Count of stations exhibiting a significant negative trend
Column 5: Characteristic of region-wide trend

PACIFIC COAST

Since 1893:

	No. stns	+ trends	- trends	region
1-day average	29	0	1	(-)
2-day average	29	0	1	(-)
Avg on non-zero days	29	0	9	--
Variability	29	1	0	(+)
Annual max	29	2	1	(+)

Number of 99 th pct exceedances	29	1	0	(-)
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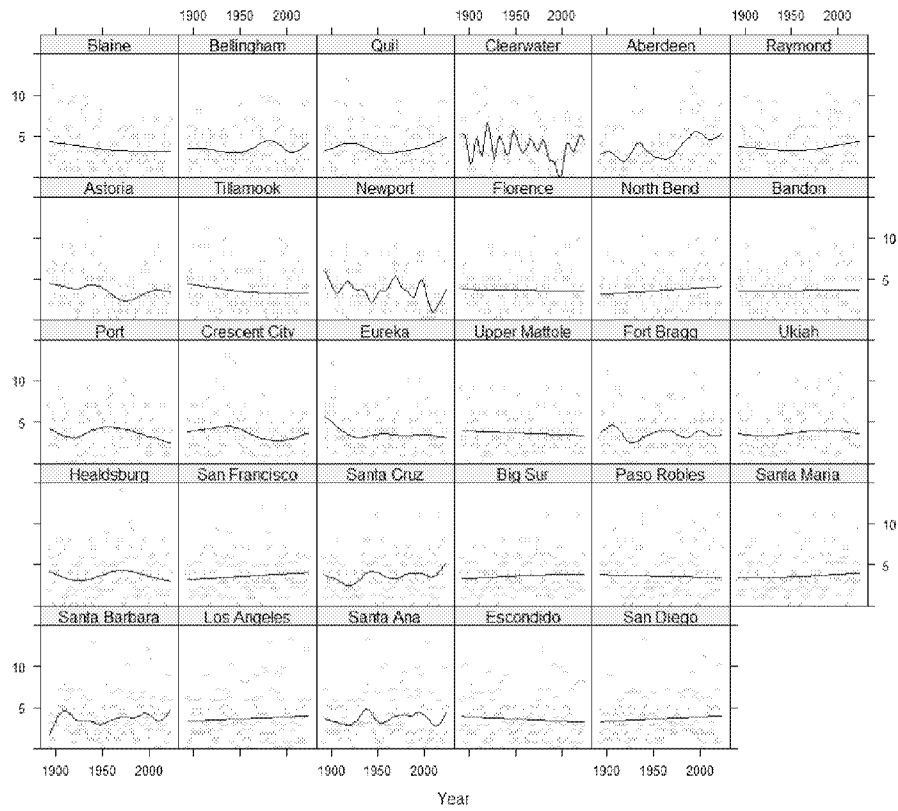
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	29	0	1	(-)
2-day average	29	0	1	(-)
Avg on non-zero days	29	0	4	(-)
Variability	29	2	3	(-)
Annual max	29	6	3	(-)
Number of 99 th pct exceedances	29	2	1	(-)

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	29	0	0	(-)
2-day average	29	0	0	(-)
Avg on non-zero days	29	0	1	(-)
Variability	29	0	0	(-)
Annual max	29	2	1	(-)
Number of 99 th pct exceedances	29	0	0	(+)

Annual No. 99th Percentile Exceedances PC 1893-2024



SOUTHEAST

Since 1873:

	No. stns	+ trends	- trends	region
1-day average	24	1	1	(+)
2-day average	24	1	1	(+)
Avg on non-zero days	24	7	2	(+)
Variability	24	1	0	(+)
Annual max	24	2	0	(+)
Number of 99 th pct exceedances	24	5	0	(+)

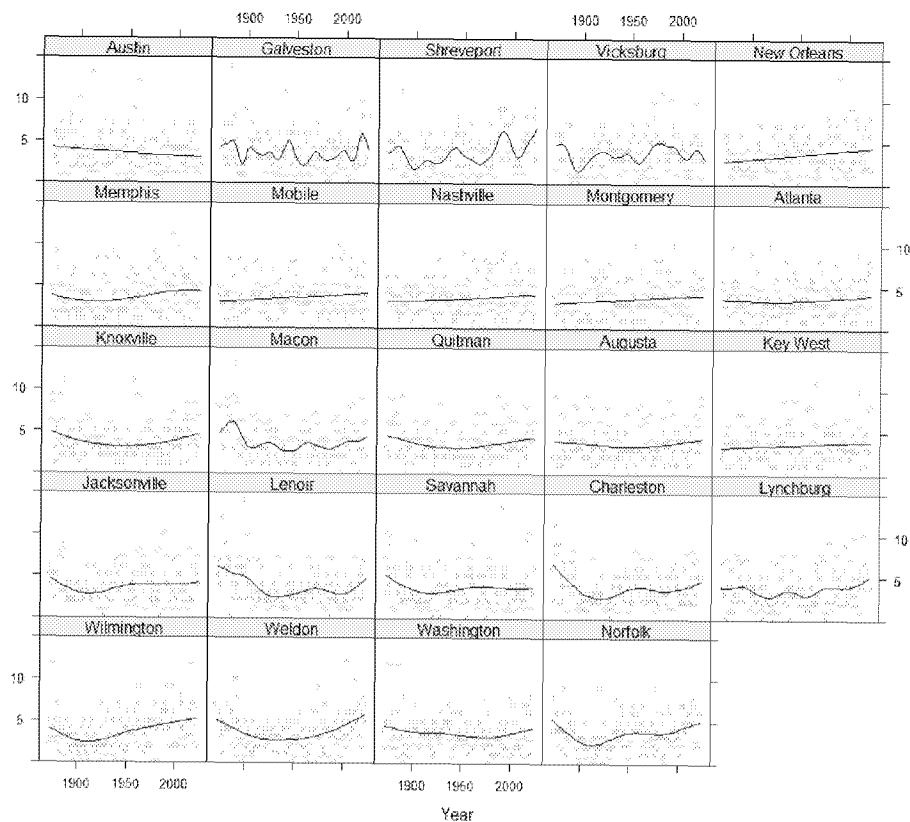
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	24	5	0	++
2-day average	24	5	0	++
Avg on non-zero days	24	5	1	++
Variability	24	6	0	++
Annual max	24	4	0	++
Number of 99 th pct exceedances	24	4	0	(+)

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	24	5	0	(+)
2-day average	24	5	0	(+)
Avg on non-zero days	24	5	1	(+)
Variability	24	3	0	(+)
Annual max	24	4	0	(+)
Number of 99 th pct exceedances	24	4	0	(+)

Annual No. 99th Percentile Exceedances SE 1873-2024



MIDWEST

Since 1893:

	No. stns	+ trends	- trends	region
1-day average	61	23	0	++
2-day average	61	23	0	++
Avg on non-zero days	61	2	12	(+)
Variability	61	12	0	++
Annual max	61	9	0	(+)
Number of 99 th pct exceedances	61	10	0	(+)

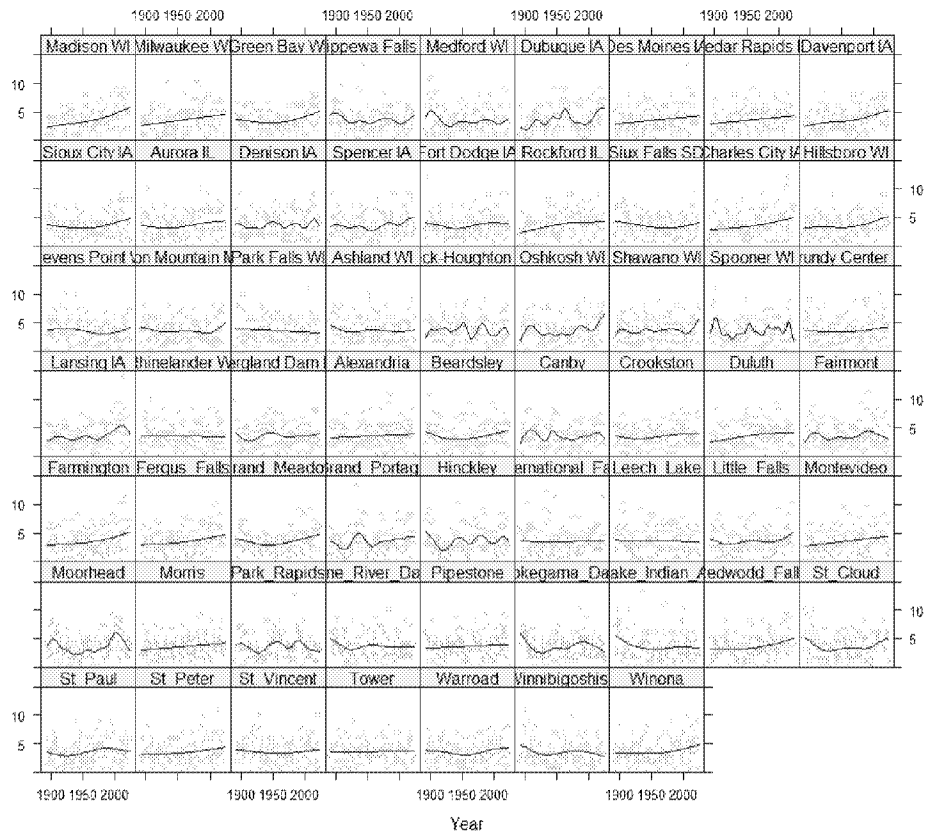
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	61	28	2	++
2-day average	61	28	2	++
Avg on non-zero days	61	11	1	++
Variability	61	16	0	(+)
Annual max	61	8	0	(+)
Number of 99 th pct exceedances	61	19	0	++

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	61	6	1	(+)
2-day average	61	6	1	(+)
Avg on non-zero days	61	8	2	(+)
Variability	61	5	1	(+)
Annual max	61	0	1	(+)
Number of 99 th pct exceedances	61	5	3	(-)

Annual No. 99th Percentile Exceedances MW 1893-2024



NORTHEAST

Since 1888:

	No. stns	+ trends	- trends	region
1-day average	27	12	0	++
2-day average	27	12	0	++
Avg on non-zero days	27	7	1	(+)
Variability	27	4	0	(+)
Annual max	27	3	0	(-)
Number of 99 th pct exceedances	27	5	0	(+)

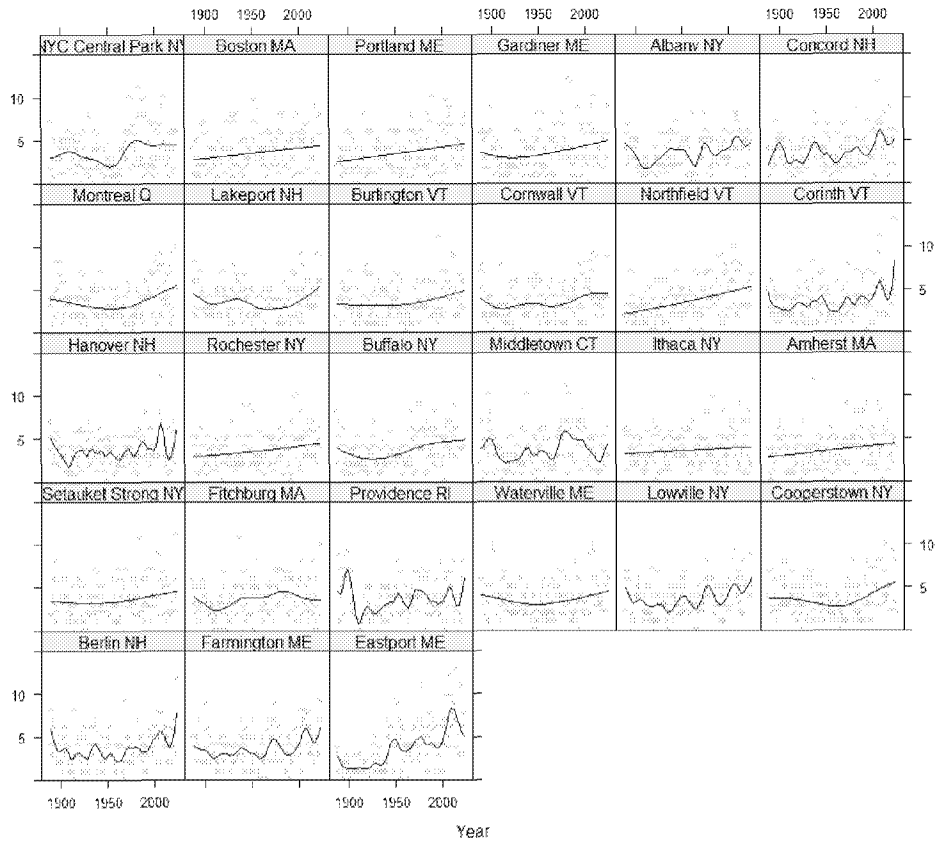
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	27	12	0	++
2-day average	27	12	0	++
Avg on non-zero days	27	7	1	(+)
Variability	27	4	0	(+)
Annual max	27	3	0	(-)
Number of 99 th pct exceedances	27	5	0	++

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	27	10	1	++
2-day average	27	10	1	++
Avg on non-zero days	27	6	0	(+)
Variability	27	2	0	(+)
Annual max	27	1	0	(+)
Number of 99 th pct exceedances	27	1	1	++

Annual No. 99th Percentile Exceedances NE 1888-2024



Review of the Fifth National Climate Assessment

[TOC \O "1-3" \H \Z \U]

1 INTRODUCTION

1.1 About this Report

This report responds to a request from OSTP Director Michael Kratsios (reproduced in Appendix XX) that we assess the suitability of the Fifth National Climate Assessment for informing climate and energy policies.

To conduct this assessment we reviewed NCA5 itself, NASEM review of the Third Order Draft and the USGCRP responses to the review. We have drawn upon our long experience working on advisory reports, including for the NASEM, IPCC and other organizations, as writers, reviewers and project leaders.

We find that NCA5 should not be relied on for policy making as it is an incomplete and misleading picture of our understanding of the changing climate and the risks it poses to the nation. NCA5 was selective and incomplete in its survey of the science as of its publication date in 2023 and has become even more so in the years since. We have reviewed many key scientific developments in a separate report to Energy Secretary Wright (Climate Working Group 2025, herein denoted "CWG25"). The overall effect of its biases and omissions is an excessively dire picture of climate risk.

Our report begins with background on the National Climate Assessments. We then discuss the standards by which we have assessed NCA5, followed by specific deficiencies that we have we've identified.

1.2 About the National Climate Assessments

The U.S. Global Change Research Program (USGCRP) was established by Presidential Initiative in 1989 and mandated by Congress in the Global Change Research Act (GCRA) of 1990 to develop and coordinate "a comprehensive and integrated United States research program which will assist the Nation and the world to understand, assess, predict, and respond to human-induced and natural processes of global change."

The National Climate Assessment (NCA) Reports evolved from the GCRA requirement to

Prepare and submit to the President and the Congress an assessment which (1) integrates, evaluates, and interprets the findings of the Program and discusses the scientific uncertainties associated with such findings; (2) analyzes the effects of global change on the natural environment, agriculture, energy production and use, land and water resources, transportation, human health and welfare, human social systems, and biological diversity; and (3) analyzes current trends in global change, both human-induced and natural, and projects major trends for the subsequent 25 to 100 years.

The five NCA Reports to date have interpreted this mandate in different ways:

- NCA1 (2000) was a multidisciplinary effort to study and portray in regional detail the potential effects of human-induced global warming on the United States.
- NCA2 (2009) was a relatively short report that not only focused on the potential consequences of climate change, but also sought to identify potential adaptation measures and identify the highest priorities for future research.

- NCA3 (2014) was an expanded effort that continued along the lines of NCA2, and was distinguished by a comprehensive review process, including a review by the National Academy of Sciences.
- NCA4 (2017/2018) was an expanded effort published in two volumes: I Climate Science Special Report, and II Impacts, Risk, and Adaptation in the United States. This was the first NCA report to devote significant effort to assessing climate science. NCA4 introduced a traceability analysis for each key finding, including a cursory description of uncertainties.
- NCA5 (2023) returned to a single volume format, reducing discussion of climate science to a cursory two chapters, with continuing with a focus on regional and sectoral impacts of climate change. NCA5 expanded its remit to topics that are arguably outside the purview of the USGCRP, focusing on “Climate Action” and policy recommendations with a social justice emphasis. NCA5’s self-description is reproduced as Appendix II.

These successive interpretations of the NCA are poorly aligned with the GCRA’s statutory requirements. Only NCA4 gives serious consideration to climate science, which receives the great majority of USGCRP funding, and even then misrepresents some important points (see the Box nearby for an example). Natural climate variability is essentially dismissed as unimportant in NCA4 and barely mentioned in NCA5 in most contexts, despite the mandate to include both human-caused and natural climate change. Most significantly, NCA5 has redirected the focus away from climate science and even the hazard elements of impacts, towards evaluation of societal vulnerabilities and advocacy for particular policy options, especially wind and solar power. The cover image for the NCA5 Report is the installation of a solar panel.

START BOX

NCA4’s Figure ES.5: A Tale of Deception and Review Failure

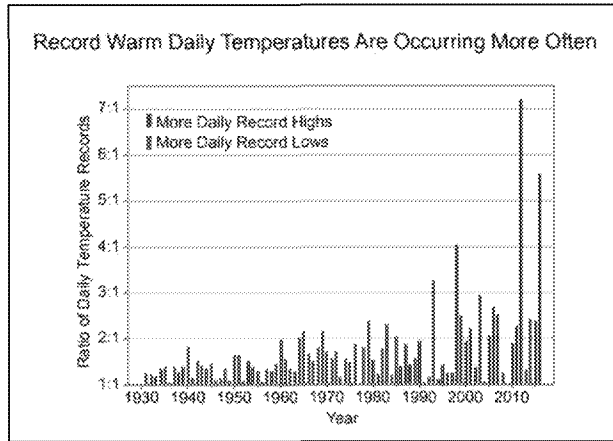
A disappointing example of NCA4’s misrepresentation of climate science involves U.S. temperature extremes. Here is a summary of the issue; details can be found in Koonin (2024).

Commented [A1]: Cite Unsettled, 2nd edition

NCA4’s Part I (Climate Science Special Report, CCSR) says (prominently and with *Very High Confidence*) on Page 19 of the Executive Summary:

There have been marked changes in temperature extremes across the contiguous United States. The number of high temperature records set in the past two decades far exceeds the number of low temperature records.

and offers this figure in support:



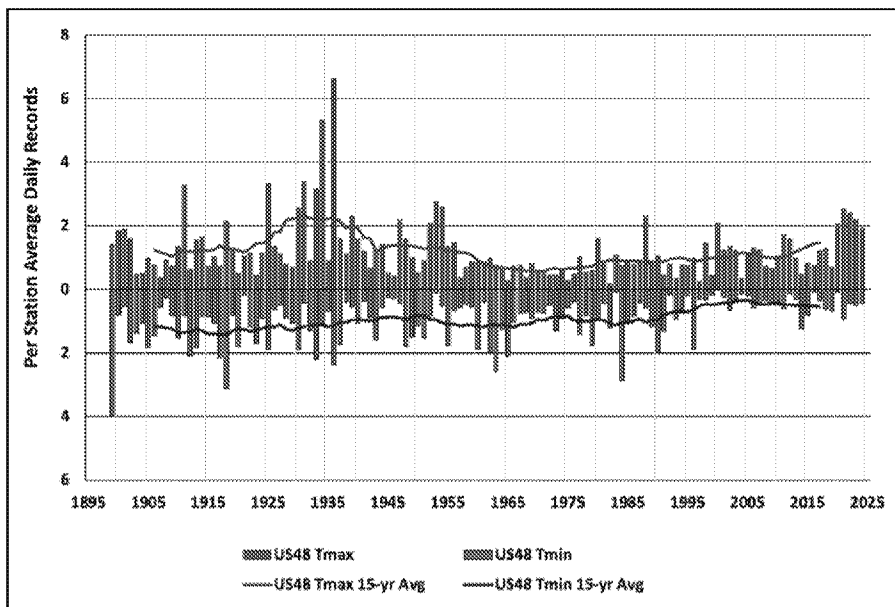
CSSR Figure ES.5 The ratio of the number of daily record high temperatures to daily record low temperatures for many stations across the 48 contiguous states is shown for each year from 1930 to 2017. The lighter bars show a year in which there were more record highs than lows, while the darker bars show years in which there were more record lows than highs. The height of the bar indicates the ratio of record highs to record lows for each year. For example, a ratio of 2:1 for a dark bar means that the stations had twice as many record daily lows as record daily highs for that year. (CSSR, 2017)

Commented [A2]: Cite CSSR

Three idiosyncratic choices combine to generate the figure's seemingly alarming rise in recent decades. First, because the record extremes tallied are defined conventionally (i.e., each more extreme than any preceding value in the history), the numbers of record highs and record lows are both expected to decline through the years (it becomes increasingly unlikely that a record will be exceeded). Second, the graph displays not the numbers of record highs and lows, but rather their ratio. And finally, the history begins only in 1930 when, in fact, data exist beginning in the late 19th Century. The upshot of these choices is that the resultant figure is guaranteed to show a long period of quiescence around followed by dramatic variations, creating the impression of large changes in recent decades, even if they aren't present.

Figure 6.3.3 of our report (reproduced below) shows the results of a proper analysis – defining each record as the singular extreme in the history, displaying numbers of warm and cold records separately, and beginning the analysis in 1899 rather than 1930. It makes evident the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. The increased heat of the past five years is too brief to be deemed climatically significant and, in any event, occurred after the CSSR was published in 2017. On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13 percent of the extreme cold events were measured. In contrast, 25 percent of the extreme Tmax records were achieved in the last quarter, in accordance with statistical expectations. As a result, the ratio shown in the CSSR explodes in recent decades. And the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate *less* prone to extremes, in sharp contrast to the title of the CSSR figure, "Record Warm Daily Temperatures Are Occurring More Often".

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Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92 percent of observations in the 126-year period since Dec 1898. US48: contiguous U.S. states. Tmax: maximum temperature. Tmin: minimum temperature.

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The National Academies' expert review panel [[HYPERLINK "https://www.nap.edu/catalog/24712/review-of-the-draft-climate-science-special-report"](https://www.nap.edu/catalog/24712/review-of-the-draft-climate-science-special-report)] the discussion of temperature extremes in a [[HYPERLINK "https://biotech.law.lsu.edu/blog/Draft-of-the-Climate-Science-Special-Report.pdf"](https://biotech.law.lsu.edu/blog/Draft-of-the-Climate-Science-Special-Report.pdf)] of the CSSR. In reference to the CSSR's Key Finding 2 of Chapter 6, they said:

Further, it is difficult to understand how a statement that includes increases in extreme warmth can be associated with a high confidence or extremely likely statement, given that most of the graphics in this chapter show a decrease in extreme warmth in the historical record.

The Federal official in charge of the CSSR (Michael Kuperberg, Executive Director of the USGCRP) [[HYPERLINK "https://science2017.globalchange.gov/PDFs/CSSR-NASresponse_110217.pdf"](https://science2017.globalchange.gov/PDFs/CSSR-NASresponse_110217.pdf)] to the Academies' review by noting that

Almost every recommendation from the NAS was incorporated [in the final version]... and a new figure was added on changes in record high and low temperatures

The “new figure” referred to is the Figure ES.5, which did not appear in the draft reviewed by the Academies’ panel. It seems unlikely that the Academies panel ever saw that figure because they surely would have commented if they had and it wouldn’t have survived to publication. And the figure’s problems were evidently not flagged (or were ignored) in the subsequent internal government reviews.

While the following statement has far less headline potential than that from the CSSR’s page 19 quoted at the beginning of this box, it has advantage of being correct:

There have been some changes in temperature extremes across the contiguous United States. The annual number of high temperature records set shows no significant trend over the past century nor over the past 40 years, but the annual number of record cold nights has declined by a factor of 4 since 1895, somewhat more rapidly in the past 30 years.

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END BOX

1.3 Standards for Assessing NCA Products

Good climate and energy policies will balance the risks and benefits of a changing climate against the world’s growing demand for reliable and affordable energy. To strike that balance, policymakers must understand at least two complex and nuanced topics –the certainties and uncertainties of climate science and the technoeconomic realities of energy systems. Experts in those subjects are the only people who can bring the facts to the discussion and so have a unique responsibility to communicate their understanding to non-experts clearly, completely, and without bias.

Expertise in energy systems resides largely in the private sector, where it is essential to providing the reliable and affordable energy services that are the lifeblood of society. Understanding is therefore continually refined and tested by the discipline of the marketplace. In contrast, climate science expertise is found largely in the non-profit realm of universities and government laboratories and so has a more academic character.

Because climate is at the core of human existence, it can engender passion and emotion. Indeed, some younger climate scientists have gone into the field to “save the planet.” So it isn’t surprising that objectivity can suffer when climate scientists communicate their understanding to non-experts. Further, the field of climate science has been politicized by NetZero mandates. When that happens, this lack of objectivity usurps the public’s right to make informed choices and undermines their confidence in the scientific enterprise.

Philip Handler, President of the National Academy of Sciences, identified the problem in a 1980 [[HYPERLINK "https://science.sciencemag.org/content/208/4448/1093"](https://science.sciencemag.org/content/208/4448/1093)] that resonates eerily four decades later:

Difficulty arises in the scientific community from confusion of the role of scientist *qua* scientist with that of scientist as citizen, confusion of the ethical code of the scientist with the obligation of the citizen, blurring the distinction between intrinsically scientific and intrinsically political questions. When scientists fail to recognize these boundaries, their own ideological beliefs, usually unspoken, easily becloud seemingly scientific debate.

In Appendix XX we include a letter of guidance from the Office of General Counsel, U.S. Department of Energy, summarizing the extent of statutory requirements governing USGCRP work products in general and NCA products in particular.

We can summarize the standards applicable to the NCA as follows:
- details.

Beyond the statutory requirements we draw attention to two other pertinent standards. President Trump's executive order of May 23, 2025, "[[HYPERLINK "https://www.whitehouse.gov/presidential-actions/2025/05/restoring-gold-standard-science/"](https://www.whitehouse.gov/presidential-actions/2025/05/restoring-gold-standard-science/)]" enumerates some of the characteristics of good science:

- i. reproducible;
- ii. transparent;
- iii. communicative of error and uncertainty;
- iv. collaborative and interdisciplinary;
- v. skeptical of its findings and assumptions;
- vi. structured for falsifiability of hypotheses;
- vii. subject to unbiased peer review;
- viii. accepting of negative results as positive outcomes; and
- ix. without conflicts of interest.

Although these should be self-evident to those trained in science, it is surprising that some have found them [[HYPERLINK "https://www.theguardian.com/commentisfree/2025/may/29/trump-american-science"](https://www.theguardian.com/commentisfree/2025/may/29/trump-american-science)].

Finally we consider that when scientific reports are being assembled that will be highly influential on climate policymaking there are other desiderata, including statements about the strength of climate knowledge. The IPCC's approach is based on judgment of the available evidence and agreement among experts. More sophisticated knowledge characterizations for risk management include: [REFERENCE AVEN](#)

- The degree to which the assumptions made are reasonable/realistic based on background knowledge—concern about the focus on implausible emissions scenarios RCP8.5/SSP5–8.5
- The degree to which data/information exists and are reliable and relevant—the historical and paleo database is inadequate for a complete characterization of natural climate variability on multi-decadal to millennial time scales
- The degree to which there is disagreement among experts (including those from different environments or academic fields)—attempts to suppress disagreement and alternative perspectives among experts

Commented [A6]: Terje Aven, "Improving Risk Characterisations in Practical Situations by Highlighting Knowledge Aspects, with Applications to Risk Matrices," Reliability Engineering & System Safety 167 (November 2017): 42–48

[[HYPERLINK "https://www.sciencedirect.com/science/article/pii/S0951832016306950"](https://www.sciencedirect.com/science/article/pii/S0951832016306950)]

- The degree to which the phenomena involved are understood and accurate models exist—concerns about the fidelity and utility of climate models
- The degree to which the knowledge has been thoroughly examined with respect to unknown knowns and—neglect of the unknown knowns associated with natural climate variability

With this background we now present our critique of NCA5.

2 OVERVIEW CHAPTER: HYPERBOLIC ADVOCACY LANGUAGE AND NON-SCIENTIFIC TONE

The opening Chapter 1 “Overview” holds a prominent place since it serves as a summary of the whole report and is all that many will read. While there is much sound scholarly content in the later sections of NCA5, Chapter 1 is marred by pervasive use of advocacy language and a tone overly focused on promoting aggressive emission reduction policies. The authors must have known this chapter would be mined for quotes by the media and activists looking to add an imprimatur of scientific authority to oversimplified declarations of opinion. Many examples can be cited; here we provide a few particularly egregious ones.

The chapter opens as follows:

The more the planet warms, the greater the impacts. Without rapid and deep reductions in global greenhouse gas emissions from human activities, the risks of accelerating sea level rise, intensifying extreme weather, and other harmful climate impacts will continue to grow. Each additional increment of warming is expected to lead to more damage and greater economic losses compared to previous increments of warming, while the risk of catastrophic or unforeseen consequences also increases.

This statement presupposes all warming is anthropogenic in origin, all warming is bad and causes economic damage, warming causes extreme weather to intensify. Such sweeping generalizations go well beyond what science has or can establish. A scientifically-sound version of this paragraph would instead say something like the following:

The Earth is undergoing a warming trend caused by a combination of natural and anthropogenic influences. This warming can be expected to generate a mix of benefits and harms that varies by region, to which society should be prepared to adapt. There is evidence that some types of extreme weather have worsened, while others have not changed or have even declined in intensity. Reducing emissions of greenhouse gases can slow the warming process although such policies have proven to be very expensive, so the costs need to be weighed against the potential benefits.

On the next page the Overview goes on to say:

Each additional increment of warming leads to greater risks [here it lists 7 key components of society including food security and the economy]... Without deeper cuts in global net emissions, climate risks to the US will continue to grow... Action to limit future warming and reduce risks can have near-term benefits and opportunities: low-carbon energy jobs, Improved air quality, Health benefits, Economic benefits...”

The authors write as if climate policy does not involve trade-offs and all measures to reduce future warming will be effective and beneficial. But the vast body of scholarship on climate science and economics does not support such simplistic claims. Not every additional increment of warming leads to economic harms, indeed (as is acknowledged in Chapter 19 on Economics) in some cases it

is expected to yield benefits. Nor is climate policy guaranteed to create jobs or benefit the economy; in many cases it has done the opposite. It is a disservice to policymakers not to be honest about this.

Page 9 promotes renewable energy options by arguing that the “levelized” costs of wind and solar power generation have fallen sharply since 2010. But “levelized” refers to the lifetime project cost averaged over all power production and ignores the intermittency problem: namely solar and wind are not always available. It results in an invalid comparison since even if, for instance, the levelized cost of solar energy per megawatt-hour falls below that of coal, coal power is available continuously and on demand whereas solar is not. The proper comparison would adjust for the difference in availability by considering the cost of supplementing solar and wind with backup natural gas-fired systems or battery storage, and on that basis renewable energy remains prohibitively expensive. Here again it is a disservice to readers not to acknowledge these facts.

Page 14 presents future emission scenarios with the following description: “Climate modeling experts develop global climate projections for a range of plausible futures.” The word “plausible” is applied to all the scenarios. The accompanying Figure includes both SSP3-7.0 and SSP5-8.5, the latter reaching the same radiative forcing as RCP8.5. The figure does not contrast observed emissions against model projections nor does it caution readers that SSP3-7.0 and SSP5-8.5 are extreme worst case scenarios that, like RCP8.5, have been heavily criticized in the scientific literature (CWG25 3.2.1). By describing the entire envelope of emission projections as “plausible” the report opens the door to later presenting impacts associated with extreme and implausible emission scenarios as part of a baseline “business-as-usual” future.

Page 17 (and elsewhere) invokes the NOAA Billion Dollar Dataset as an indicator of weather getting worse. Scientists have shown that this is an invalid metric (CWG 10.2) since it measures the growth of the economy not the frequency of extreme weather, and indeed NOAA has withdrawn the data product. Even though it was still distributed by NOAA at the time of the NCA5, the report authors should have assessed it skeptically and seen that it was unfit for the purpose of measuring climate trends.

Page 23 states, in large font:

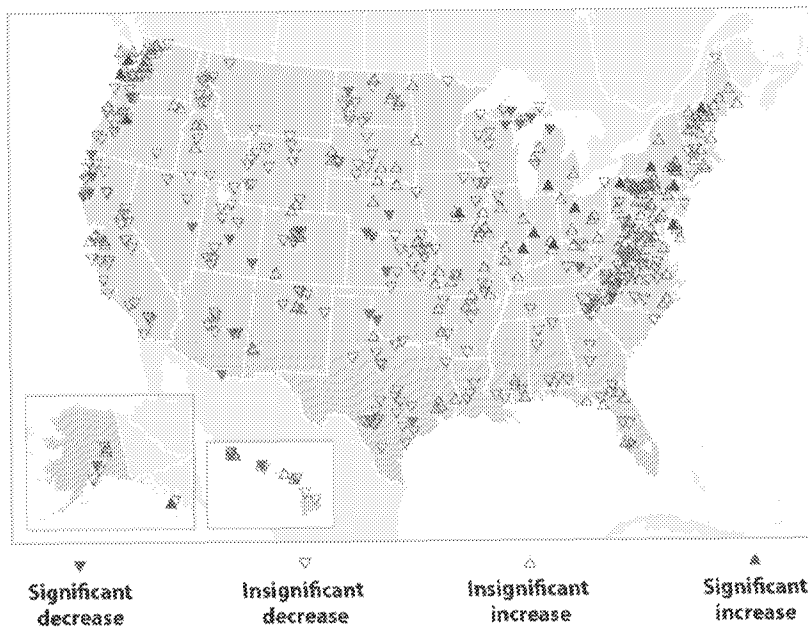
Climate changes are making it harder to maintain safe homes and healthy families; reliable public services; a sustainable economy; thriving ecosystems, cultures, and traditions; and strong communities.

It is pointless to try to evaluate this statement on scholarly grounds; it is self-evidently hyperbolic. This kind of language doesn’t belong in a scientific assessment report. Its prominent inclusion points not only to the willingness of NCA5 authors to promote hysteria, but also the ineffectiveness of the review process at not ensuring such statements are removed.

We won’t try to cite all the remaining examples of advocacy and hyperbole in the Overview chapter; one more example will suffice. Page 26 states “Increasing flooding puts more people and assets at risk.” The accompanying figure contrasts model-projected flood losses by county in 2050 to that observed in 2020 as estimated in Wing *et al.* (2022)¹. Hence the evidence for the claim is not currently-observed trends, it is a model-generated projection of changes. But current trends in U.S.-

¹ Wing, Oliver, William Lehman, Paul Bates *et al.* (2022) Inequitable patterns of US flood risk in the Anthropocene. *Nature Climate Change* 12 156–162 [[HYPERLINK "https://www.nature.com/articles/s41558-021-01265-6"](https://www.nature.com/articles/s41558-021-01265-6)]

based flooding reveal a more complex picture with a general overall trend towards less flooding. The Environmental Protection Agency's "Climate Change Indicators: River Flooding" webpage² shows maps both of flood magnitude and frequency. Both show more regions experiencing declines over 1965-2015 than increases. Hence current trends indicate generally declining U.S. flood risks, but the NCA5 Overview not only fails to mention this but declares the opposite based on a single study presenting model-generated forecasts of flood activity decades in the future.



U.S. Flood magnitude trends 1965-2015.

Source: [HYPERLINK "<https://www.epa.gov/climate-indicators/climate-change-indicators-river-flooding>"]

² [HYPERLINK "<https://www.epa.gov/climate-indicators/climate-change-indicators-river-flooding>"]

3 ONE-SIDED OVERSIMPLIFICATIONS IN SCIENCE SUMMARY CHAPTERS

Chapters 2 (Climate Trends) and 3 (Earth Systems Processes) form the scientific core of NCA5. As we will show in the following examples they fail to meet statutory requirements to discuss scientific uncertainties and the role of natural variability, and they fail to meet the more stringent implicit standards expected of a policymaking report.

3.1 Increased Lower Bound of Climate Sensitivity

The promotional tone of Chapter 1 is carried forward into Chapter 3 (Earth System Processes) where, on page 3-10, Key Message 3.2 states “The Estimated Range of Climate Sensitivity Has Narrowed by 50%”. Referring to Equilibrium Climate Sensitivity (ECS) the section elaborates:

Recent improvements in the understanding of how climate feedbacks vary across timescales have narrowed the estimated *likely* range of warming expected from a doubling of atmospheric carbon dioxide by 50% to between 4.5°F and 7.2°F (*high confidence*).... This uncertainty reduction results from advances in combining observations and targeted modeling results from nearly independent lines of evidence, each of which generally agrees on the values of ECS. The lines of evidence include 1) observed present-day variations on monthly to interannual timescales from which cloud and other climate feedbacks are inferred; 2) observed temperature changes between the preindustrial period and present and associated relationships to ERF; and 3) estimated temperature and radiative forcing changes for multiple warm and cold periods in paleoclimate records.

The graphic summary on page 3-11 states

The reduced uncertainty in climate sensitivity and climate feedback has been achieved through unprecedented quantitative synthesis of evidence from observed changes over recent decades, the industrial era, and paleoclimate.

This is a very inadequate description of the situation. The key development in AR6 was a *reduction* of confidence in the ability of climate models to identify ECS and the shift away from the model-based method the IPCC had relied on since AR1 in 1990. The IPCC instead turned to data-driven ECS estimation and specifically chose a single paper from the scientific literature, Sherwood *et al.* (2020³) for the purpose. It combined paleoclimate data, modern instrumental data and modern observations of climate processes, mainly cloud-related, that govern key feedbacks. Sherwood *et al.* used a subjective Bayesian method to determine the likely range of ECS values. The Bayesian approach begins with the researcher specifying a “prior”, namely an expectation of what the answer will be before seeing the data. In this case the prior consists of an expected ECS range based on the researchers’ subjective beliefs. Then the data are allowed to influence the ECS distribution and the final result is a weighted average of the assumed prior and the data-driven result. Sherwood *et al.* found a best (or median) ECS estimate of 5°F (3°C), which was close to previous model-based

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³ Sherwood, S. C., Bony, S., Boucher, O., Bretherton, C. S., Forster, P. M., Gregory, J. M., & Stevens, B. (2020). An assessment of Earth's climate sensitivity using multiple lines of evidence. *Reviews of Geophysics*, 58(4). [HYPERLINK "https://doi.org/10.1029/2019rg000678"]

estimates but raised the likely lower bound by 1.7°F from 2.5°F to 4.2°F. The IPCC accepted this result and increased the best estimate to 3.1°C.

The NCA5 was published in November 2023. Well before that, in September 2022, Lewis (2023) had been published online at *Climate Dynamics* presenting a forceful critique of Sherwood *et al.*⁴ One of Lewis' points was that Sherwood *et al.*'s result was dependent on their chosen subjective prior. Lewis recommended using an objective Bayesian method, which places primary weight on the data rather than the researcher's expectation. Using that and updated forcing data from AR6, Lewis estimated an ECS best estimate of 3.7°F (2.2°C) with a likely lower bound of 2.7°F (1.6°C).

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Hence, in contrast to the promotional language of Chapter 3 a more valid summary of the ECS literature as it stood at the time of writing the NCA5 would be what we wrote in CWG25 (emphasis added):

For the AR6, the IPCC placed primary weight on the results of Sherwood *et al.* (2020) that combined historical and paleoclimate proxies with the process-based approach and yielded a best estimate of 3.1°C with a *likely* range of 2.6–3.9°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood *et al.* analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). **The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent.** The most recent publications on the debate between Sherwood *et al.* and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

3.2 Presenting New Emission Scenarios as a Scientific “Advance”

Chapter 3 pp. 13–14 treats the release of new emission scenarios as a scientific “advance” without addressing the failure of many previous scenarios to match reality or providing an honest assessment of the likelihood that the new ones are biased in the same way.

Key Message 3.3 states “New Data and Analysis Methods Have Advanced Climate Science” and includes the following:

New scenarios of socioeconomic development, and their associated emissions and land-use changes, drive updated climate projections from Earth system models. The Scenario Model Intercomparison Project (ScenarioMIP) organized the main set of 21st-century projection experiments under the latest phase of the Coupled Model Intercomparison Project, CMIP6. These CMIP6 projections used newly developed scenarios based on Shared Socioeconomic Pathways (SSPs; Figure 3.4). Five SSPs represent alternative plausible trajectories of 21st-century GDP and population growth and the pace and pervasiveness of socioeconomic and technological progress within individual nations and across the world (see Table 3 in the Guide to the Report). SSP-specific drivers are used in integrated assessment models (IAMs)

⁴ Lewis, N. (2023). Objectively combining climate sensitivity evidence. *Climate Dynamics*, 61(9–10), 3155–3163. [HYPERLINK "https://doi.org/10.1007/s00382-022-06398-8"]. The final citation for this paper is Lewis (2023) because the print edition did not appear until 2023, but the article was accepted in August 2022 and the online edition appeared and was in circulation in September 2022.

to simulate the corresponding evolution of the energy system and the resulting greenhouse gas trajectories. These are in turn used by ESMs to drive their 21st-century projections.

There is nothing wrong with NCA5 discussing the development of new emission scenarios which serve as inputs to climate change projections and impact studies. But it is a serious omission not to inform the reader of the failure of many previous IPCC scenarios to match reality and the tendency of the scenario groups to exaggerate near-term and long-term CO₂ concentration growth (CWG25 3.2.1). It is also a serious omission not to caution readers that many climate impact studies use RCP8.5 which by the time of NCA5 had already been heavily criticized in the literature.

The same section also reports the availability of new and larger model ensembles as a scientific advance, without addressing ways in which models are getting worse in some key respects (CWG Ch 5).

3.3 Uncritical Promotion of “Emergent Constraints”

Chapter 3 page 17 presents the topic of “emergent constraints” in uncritical terms:

An approach to reduce uncertainty in climate change projections has matured over the past decade. It is known as “emergent constraints.” The term refers to strong statistical relationships between highly uncertain future climate parameters and observable trends or variations in the current climate, along with a physical explanation of this relationship.

Emergent constraints appeared in the climate modeling literature as a way to tie GCM behavior to climate observations in hopes of generating insight into real-world ECS. Climate models exhibit a wide range of sensitivities. The idea of emergent constraints is to examine whether the models with shared sensitivity values also share a common representation of some climate process (usually related to clouds) that might indirectly influence ECS. Suppose, for instance, that in low-ECS models the total cloud fraction in the tropics is strongly correlated with that in the southern midlatitudes but in high-ECS models the correlation is weak. Then researchers could check if the observed correlation is strong or weak and draw a conclusion about which type of model, and therefore which ECS value, is more likely.

A problem in the emergent constraint literature is that there has been a large proliferation of proposed correlations with little physical motivation. Many emergent constraints patterned on CMIP5 models failed to work on CMIP6 models (Schlund *et al.* 2020)⁵. In other words, the observed correlations in CMIP5 models between ECS and cloud processes failed to show up in CMIP6 models, indicating that they were likely spurious rather than clues to physical processes governing the Earth climate system. The result was that emergent constraints estimated on CMIP5 models widened the range of estimated ECS values when applied to CMIP6 models.

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Schlund *et al.* summarized the problem as follows:

In this study, we systematically analyze 11 published emergent constraints on ECS that have mostly been derived from models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5) project... The focus of the study is on testing if these emergent

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⁵ Schlund, Manuel, Axel Lauer, Pierre Gentine, Steven C. Sherwood, and Veronika Eyering (2020) Emergent constraints on equilibrium climate sensitivity in CMIP5: do they hold for CMIP6? *Earth System Dynamics* 11 1233-1258 [[HYPERLINK "https://doi.org/10.5194/esd-11-1233-2020"](https://doi.org/10.5194/esd-11-1233-2020)]

constraints hold for [Earth System Models] participating in the new Phase 6 (CMIP6). Since none of the emergent constraints considered here have been derived using the CMIP6 ensemble, CMIP6 can be used for cross-checking of the emergent constraints on a new model ensemble. **The application of the emergent constraints to CMIP6 data shows a decrease in skill and statistical significance of the emergent relationship for nearly all constraints, with this decrease being large in many cases.** Consequently, the size of the constrained ECS ranges (66% confidence intervals) widens by 51% on average in CMIP6 compared to CMIP5.

Yet NCA5 described the use of emergent constraint analysis as a great “advance” that reduced uncertainty.

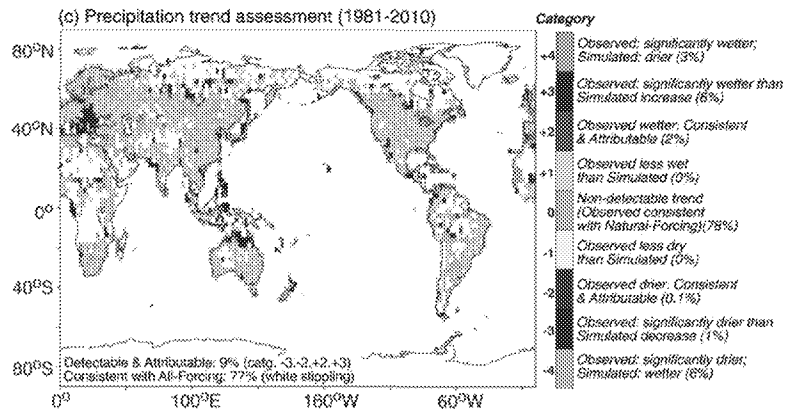
3.4 Overstating Findings in Underlying Sources

Although we did not do a detailed audit of the NCA5’s use of source material, a few spot checks turned up evidence of a pattern of overstatement.

Chapter 2 page 11 reports on an increase in precipitation in central and eastern US based on a comparison of 2002-2021 average rainfall to the average over 1901-1960. Note that this a non-standard metric; we will discuss NCA5’s inconsistent choices of time scales of analysis below. The change in this case is called a “trend” even though this is not how a trend is measured, and says that it is “attributable to climate change”. The claims were attributed to the following paper:

- Knutson, Thomas and Fanrong Zeng (2018) “Model Assessment of Observed Precipitation Trends over Land Regions: Detectable Human Influences and Possible Low Bias in Model Trends” *Journal of Climate* 31(12) [[HYPERLINK "https://journals.ametsoc.org/view/journals/clim/31/12/jcli-d-17-0672.1.xml"](https://journals.ametsoc.org/view/journals/clim/31/12/jcli-d-17-0672.1.xml)]

But Knutson and Zeng did not say these things. It examined linear trends over 1901 – 2010, 1951 – 2010 and 1981 – 2010. It did not compare average rainfall over 2002 - 2021 to average rainfall over 1901 – 1960, indeed it was published in 2018 so it could not have. With regard to 1981-2010 trends its results were summarized in the following figure:



Gray indicates no trends detected. Stippling means that there were no trends in the models either so the models and observations agreed in that respect. Detectable and attributable trends were found over only 9% of the land surface of the Earth. Over the US there are detectable trends over only a few regions in the Southwest.

Chapter 2 page 18 states

There is robust evidence that human-caused warming has contributed to increases in the frequency and severity of the heaviest precipitation events across nearly 70% of the US.

This is attributed to two papers:

- Diffenbaugh, N.S., D. Singh, and J.S. Mankin, 2018: Unprecedented climate events: Historical changes, aspirational targets, and national commitments. *Science Advances*, 4 (2), 3354. [[HYPERLINK "https://doi.org/10.1126/sciadv.aao3354"](https://doi.org/10.1126/sciadv.aao3354)]

and

- Kirchmeier-Young, M.C. and X. Zhang, 2020: Human influence has intensified extreme precipitation in North America. *Proceedings of the National Academy of Sciences of the United States of America*, 117 (24), 13308-13313. [[HYPERLINK "https://doi.org/10.1073/pnas.1921628117"](https://doi.org/10.1073/pnas.1921628117)]

Diffenbaugh et al. presented ratios of observed occurrences of extreme events to simulated occurrence rates in CMIP6 models run with only natural forcings. They report that for 79% of the U.S. extreme rainfall event frequencies are currently higher than in model simulations, and the ratio of occurrences will rise under future warming simulations. This is not “robust” evidence of anthropogenic influence since it requires readers to assume that climate models provide accurate simulations of regional precipitation patterns, something which even the IPCC AR6 admits is uncertain (AR6 WGI SPM Box SPM 1.2, SPM Section C.1.3).

Kirchmeier-Young and Zhang looked at extreme 1- and 5-day events in North America and, using 3 GCMs, found “A signal of combined anthropogenic and natural external forcing can be detected in the intensification of extreme precipitation at the continental scale over North America. In some cases, this intensification can be attributed to human influence specifically.” However, they noted large differences among the three models in their simulated precipitation changes. Also, 2 of the 3 models failed to yield detection for Rx5Day for the North America mean. Finally, the authors used Total Least Squares, an estimation method known to overstate signal detection results (CWG Section 8.3.2) . Here again this is not “robust” evidence, it is suggestive but other studies have found natural variability predominant.

4 RELIANCE ON *Ad Hoc* TIME SCALES FOR TREND ANALYSIS

In CWG25 Chapter 6 we discussed the need to be careful regarding the choice of time scale when making claims about trends in extreme weather. We gave examples from analysis of river flooding (6.1), heatwaves (6.3) and extreme precipitation (6.4) to show how assertions about apparent trends based on short data sets fall apart when looking at longer versions of the same data sets. Here we elaborate on these examples to illustrate a general point that NCA5 made inconsistent and *ad hoc* choices about time scales of analysis, weakening the validity of their conclusions.

4.1 Average and Extreme Precipitation

McKittrick and Christy (2019)⁶ showed that apparently significant positive trends in U.S. average and extreme precipitation over the NCA4 interval (1901 – 2016) disappeared on longer samples (extending back as far as the 1840s depending on location or on a shorter interval coinciding with the final 40 years of the data then available (1978 – 2017).

In CWG Section 6.4 we presented analysis of updated data for the same locations and many more besides, in all cases finding considerable regional heterogeneity and lack of robustness of trends to use of long samples.

NCA5 did not continue the NCA4 precedent of using the post-1901 interval as the time scale for its precipitation discussion, instead it refers to changes “since the 1950s” which we take to mean 1950 onwards. For the present report we have extended the analysis even further now to include 141 stations across the US in the Pacific Coast, Southwest, Midwest, Northeast and Southeast regions. We provide details in the Appendix; here we note merely that once again it is possible to find trends that support the NCA5 position, but they are not robust to selecting longer or shorter time scales of analysis. Data from 1950 to 2024 yields many indications of increased average and extreme precipitation at individual stations and region-wide averages. But when using the entire data set (back to the 1890s or earlier depending on location) or the later subset (1980 to 2024) the trends become smaller, in many cases they become statistically insignificant, and occasionally they change sign. Only in the Northeast region are the post-1950 trends robust to focusing on the post-1980 interval.

Under Key Message 2.2 “Extreme Events Are Becoming More Frequent and Severe” (p. 2-16) NCA5 states (p. 2-18):

“Rainfall is becoming more extreme”

Since the 1950s, there has been an upward trend in heavy precipitation across the contiguous US. This increase is driven largely by more frequent precipitation extremes, with relatively smaller changes in their intensity. The largest increase in the number of extreme precipitation days (defined as the top 1% of heaviest precipitation events) has occurred over the Northeast (an increase of around 60%) and Midwest (around 45%), along with increases of more than 10% in their annual and 5-year maximum amount

⁶ McKittrick, R., and J.R. Christy (2019). Assessing changes in US regional precipitation on multiple time scales. *Journal of Hydrology*, 578, 124074. [[HYPERLINK "https://doi.org/10.1016/j.jhydrol.2019.124074"](https://doi.org/10.1016/j.jhydrol.2019.124074)]

(Figure 2.8). These changes have contributed to increases in river and stream flooding in these regions. The increase in frequency and intensity of precipitation extremes is evident across a broad range of event durations (from 1 to 30 days) and return intervals (1 to 20 years), particularly east of the Rocky Mountains.

There is robust evidence that human-caused warming has contributed to increases in the frequency and severity of the heaviest precipitation events across nearly 70% of the US. Paleoclimate records derived from tree-ring growth provide evidence that summer moisture has increased over the past century in parts of New England, the central-eastern US, and the northern Mississippi River valley.

The following is a more accurate summary of what U.S. data show.

There are regionally-heterogeneous changes in average and extreme precipitation. Positive trends in annual average rainfall and extreme events (defined either as the annual maximum or the number of exceedances of the 99th percentile value) are generally weak or non-existent when looking at samples exceeding 130 years in length. Significant trends can be found when beginning the sample in the 1950s although in most cases the trends weaken and become insignificant when looking at the post-1980 interval. This makes attribution to anthropogenic warming difficult.

Along the Pacific coast very few stations (1 or 2 out of 29) exhibit significant trends on any time scale in any metric and the region-wide trends are insignificant. In the Southeast region about 5 out of 24 stations exhibit positive trends in average and extreme precipitation metrics and the regional trends are likewise significant, but only on samples beginning in 1950. When the sample starts in 1873 or 1980 the trends weaken and become mostly insignificant. In the Midwest region nearly half the stations exhibit positive and significant trends in average precipitation since 1893 (23/61) and 1950 (28/61) but the trends weaken after 1980: only 6/61 locations are significant and the region-wide trend is insignificant. Regional trends in max and 99th percentile exceedances are insignificant post-1893 and -1980 but the latter are positive and significant post-1950.

In the Northeast region 12 out of 27 stations exhibit positive and significant increases in average precipitation post-1888, post-1950 and post-1980 (10/27) and the regional trend is positive and significant in all three intervals. The regional number of 99th percentile exceedances has a positive trend post-1950 and post-1980 but not post-1888. The significant positive trends post-1980 are concentrated in NH but are insignificant elsewhere.

Consequently, precipitation in the U.S. exhibits considerable regional and temporal variability. Relatively more places became wetter than drier. In the Midwest and Northeast the general pattern since 1950 favors increased precipitation depending on the location, although trends since 1980 have not tended to be statistically significant.

4.2 Heatwaves

- details; NCA4 used entire 20th century while NCA5 looked at post-1960 interval

5 INADEQUATE TRACEABLE ACCOUNTS

- details

6 OVERCONFIDENCE WHEN STATING CONCLUSIONS

- details

7 RELIANCE ON EXTREME SCENARIOS

-details

8 BIASED SELECTION OF REFERENCES

-details

9 SUMMARY: EVALUATING OF THE NCA5

9.1 Pertinent aspects when evaluating in light of statutory requirements

- not our remit to make a ruling but here are aspects to consider in light of statutory requirements

9.2 Evaluation from the perspective of expert users of the report

- we have deep knowledge of the topics surveyed by the NCA5 authors
- we do not have confidence that the report was balanced and comprehensive
- we can point to many specific instances in which the report did not exhibit an appropriate level of quality or integrity as a scientific document
- we have reason to believe the whole process, from author selection to handling of expert reviews, was biased towards reinforcing foregone conclusions and alarmist messaging

9.3 Evaluation from the perspective of citizens interested in good policymaking

- Public concerns about climate change are valid, as are concerns about cost of living, economic growth, employment, etc.
- We share the general concern that elected officials and those who serve them have the best information available when making important decisions around energy and climate policy
- NCA5 was a missed opportunity: it could have been a valuable input to that process but it did not turn out that way
- consequently its usage is unlikely to lead to better decisions and would more likely increase the error rate in policy formation and we recommend it not be used for policymaking purposes.

APPENDIX 1: Seth's letter on statutory requirements for NCA5

APPENDIX 2: Analysis of 141 U.S. Longterm Daily Precipitation Records.

Table codes: (-) neg insignificant, -- neg significant, (+) pos insignificant, ++ pos significant.

Column 1: Measure

Column 2: Number of stations in that region

Column 3: Count of stations exhibiting a significant positive trend

Column 3: Count of stations exhibiting a significant negative trend

Column 5: Characteristic of region-wide trend

PACIFIC COAST

Since 1893:

	No. stns	+ trends	- trends	region
1-day average	29	0	1	(-)
2-day average	29	0	1	(-)
Avg on non-zero days	29	0	9	--
Variability	29	1	0	(+)
Annual max	29	2	1	(+)
Number of 99 th pct exceedances	29	1	0	(-)

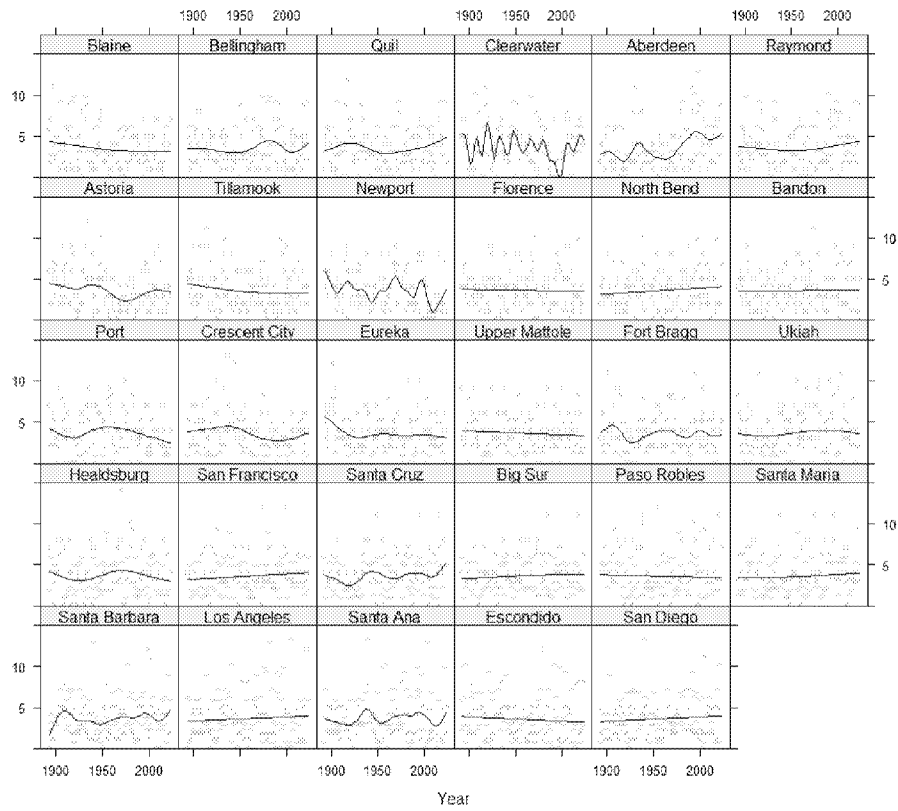
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	29	0	1	(-)
2-day average	29	0	1	(-)
Avg on non-zero days	29	0	4	(-)
Variability	29	2	3	(-)
Annual max	29	6	3	(-)
Number of 99 th pct exceedances	29	2	1	(-)

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	29	0	0	(-)
2-day average	29	0	0	(-)
Avg on non-zero days	29	0	1	(-)
Variability	29	0	0	(-)
Annual max	29	2	1	(-)
Number of 99 th pct exceedances	29	0	0	(+)

Annual No. 99th Percentile Exceedances PC 1893-2024



SOUTHEAST

Since 1873:

	No. stns	+ trends	- trends	region
1-day average	24	1	1	(+)
2-day average	24	1	1	(+)
Avg on non-zero days	24	7	2	(+)
Variability	24	1	0	(+)
Annual max	24	2	0	(+)
Number of 99 th pct exceedances	24	5	0	(+)

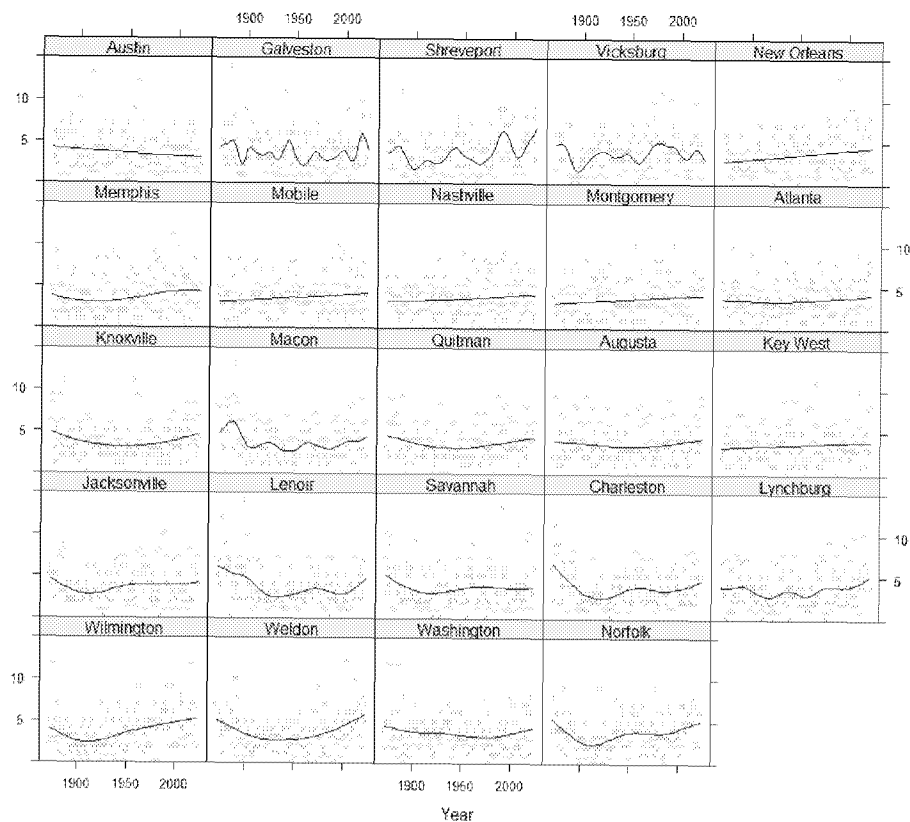
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	24	5	0	++
2-day average	24	5	0	++
Avg on non-zero days	24	5	1	++
Variability	24	6	0	++
Annual max	24	4	0	++
Number of 99 th pct exceedances	24	4	0	(+)

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	24	5	0	(+)
2-day average	24	5	0	(+)
Avg on non-zero days	24	5	1	(+)
Variability	24	3	0	(+)
Annual max	24	4	0	(+)
Number of 99 th pct exceedances	24	4	0	(+)

Annual No. 99th Percentile Exceedances SE 1873-2024



MIDWEST

Since 1893:

	No. stns	+ trends	- trends	region
1-day average	61	23	0	++
2-day average	61	23	0	++
Avg on non-zero days	61	2	12	(+)
Variability	61	12	0	++
Annual max	61	9	0	(+)
Number of 99 th pct exceedances	61	10	0	(+)

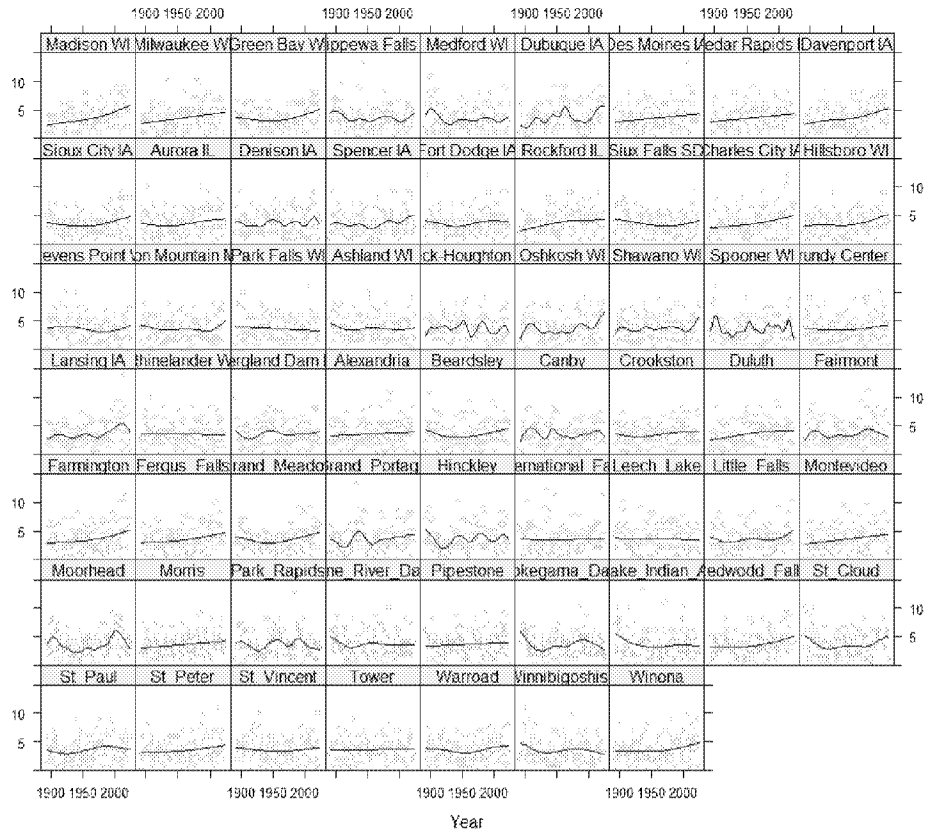
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	61	28	2	++
2-day average	61	28	2	++
Avg on non-zero days	61	11	1	++
Variability	61	16	0	(+)
Annual max	61	8	0	(+)
Number of 99 th pct exceedances	61	19	0	++

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	61	6	1	(+)
2-day average	61	6	1	(+)
Avg on non-zero days	61	8	2	(+)
Variability	61	5	1	(+)
Annual max	61	0	1	(+)
Number of 99 th pct exceedances	61	5	3	(-)

Annual No. 99th Percentile Exceedances MW 1893-2024



NORTHEAST

Since 1888:

	No. stns	+ trends	- trends	region
1-day average	27	12	0	++
2-day average	27	12	0	++
Avg on non-zero days	27	7	1	(+)
Variability	27	4	0	(+)
Annual max	27	3	0	(-)
Number of 99 th pct exceedances	27	5	0	(+)

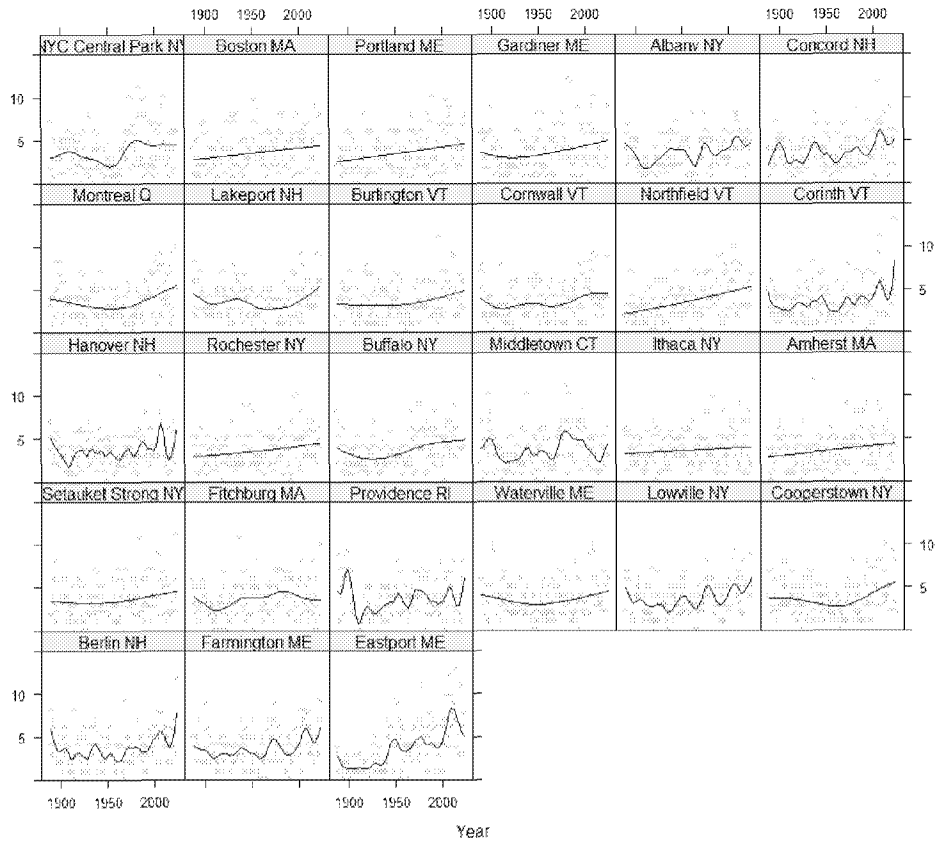
Since 1950:

	No. stns	+ trends	- trends	region
1-day average	27	12	0	++
2-day average	27	12	0	++
Avg on non-zero days	27	7	1	(+)
Variability	27	4	0	(+)
Annual max	27	3	0	(-)
Number of 99 th pct exceedances	27	5	0	++

Since 1980:

	No. stns	+ trends	- trends	region
1-day average	27	10	1	++
2-day average	27	10	1	++
Avg on non-zero days	27	6	0	(+)
Variability	27	2	0	(+)
Annual max	27	1	0	(+)
Number of 99 th pct exceedances	27	1	1	++

Annual No. 99th Percentile Exceedances NE 1888-2024





Impacts of Carbon Dioxide Emissions on the U.S. Climate

CONFIDENTIAL DRAFT FOR DISCUSSION PURPOSES

Ad hoc Climate Working Group
United States Department of Energy
May 28, 2025

CONFIDENTIAL DRAFT FOR DISCUSSION PURPOSES

Impacts of Carbon Dioxide Emissions on the U.S. Climate

Report to US Energy Secretary Christopher Wright

May 28, 2025

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Ad hoc Climate Working Group (2025) Impacts of Carbon Dioxide Emissions on the U.S. Climate.
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SECRETARY'S FOREWORD

Energy, Integrity, and the Power of Human Potential

Over my lifetime, I've had the privilege of working as an energy entrepreneur across a range of fields—nuclear, geothermal, natural gas, and more—and I now serve as Secretary of Energy under President Donald Trump. But above all, I'm a physical scientist who sees modern energy as nothing short of miraculous. It powers every aspect of modern life, drives every industry, and has made America an energy powerhouse with the ability to fuel global progress.

The rise of human flourishing over the past two centuries is a story worth celebrating. Yet we are told—relentlessly—that the very energy systems that enabled this progress now pose an existential threat. Hydrocarbon-based fuels, the argument goes, must be rapidly abandoned or else we risk planetary ruin.

That view demands scrutiny. That's why I commissioned this report: to encourage a more thoughtful and science-based conversation about climate change and energy. With my technical background, I've reviewed reports from the Intergovernmental Panel on Climate Change, the U.S. government's assessments, and the academic literature. I've also engaged with many climate scientists, including the authors of this report.

What I've found is that media coverage often distorts the science. Many people—even well-meaning ones—walk away with a view of climate change that is exaggerated or incomplete. To provide clarity, I asked a diverse team of independent experts to summarize the current state of climate science, with a focus on how it relates to the United States.

I didn't select these authors because we always agree—far from it. In fact, they may not always agree with each other. But I chose them for their rigor, honesty, and willingness to elevate the debate. I exerted no control over their conclusions. What you'll read are their words, drawn from the best available data and scientific assessments.

I've reviewed the report carefully and challenged its findings. I believe it faithfully represents the state of climate science today. Still, many readers may be surprised by its conclusions—which differ in important ways from the mainstream narrative. That's a sign of how far the public conversation has drifted from the science itself.

To correct course, we need open, respectful, and informed debate. That's why I'm inviting public comment on this report. Honest scrutiny and scientific transparency should be at the heart of our policymaking.

Climate change is real, and it deserves attention. But it is not the greatest threat facing humanity. That distinction belongs to global energy poverty. As someone who values data, I know that improving the human condition depends on expanding access to reliable, affordable energy. Climate change is a challenge—not a catastrophe. But misguided policies based on fear rather than facts could truly endanger human well-being.

We stand at the threshold of a new era of energy leadership. If we empower innovation rather than restrain it, America can lead the world in providing cleaner, more abundant energy—lifting billions out of poverty, strengthening our economy, and improving our environment along the way.

EXECUTIVE SUMMARY

This report reviews scientific certainties and uncertainties in how anthropogenic carbon dioxide (CO₂) emissions have affected, or will affect, the Nation's climate, extreme weather events, and selected metrics of societal well-being. Those emissions are increasing the concentration of CO₂ in the atmosphere through a complex and variable carbon cycle, where some portion of the additional CO₂ persists in the atmosphere for centuries.

Elevated concentrations of CO₂ enhance plant growth, globally "greening" the planet and increasing agricultural productivity. They also decrease ocean alkalinity by an amount within the range of natural variability. That is possibly detrimental to coral reefs, although the recent rebound of the Great Barrier Reef suggests otherwise.

Carbon dioxide also acts as a greenhouse gas, exerting a warming influence on climate and weather. The world's several dozen detailed climate models offer little guidance on how the climate responds to that influence, with the average surface warming under a doubling of the CO₂ concentration ranging from 1.8°C to 5.7°C, generally higher than simpler, data driven estimates, which suggest 1.8°C

Detailed climate models generally run "hot" in their description of the climate of the past few decades - too much warming at the surface, in the lower- and mid-troposphere, and too much amplification of warming aloft. They also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The combination of overly sensitive models and extreme scenarios for future emissions has exaggerated projections of future warming.

Most extreme weather events do not show long-term trends. Claims of increased frequency or intensity of hurricanes, tornadoes, floods, and droughts are not supported by historical data. Additionally, forest management practices are an often-overlooked factor in assessing wildfire activity. Global sea level has risen approximately 8 inches since 1900, but there are significant regional variations in tide gauge data driven primarily by local land subsidence; U.S. tide gauge measurements in aggregate do not show any long-term sea level acceleration.

The attribution of particular climate changes or extreme weather events to human CO₂ emissions is challenged by natural climate variability, data limitations, and inherent model deficiencies. Moreover, solar activity's contribution to the warming climate may be underestimated.

Both models and experience suggest that CO₂-induced warming may be less significant economically than commonly believed, and excessively aggressive mitigation policies could prove more detrimental than beneficial. Social Cost of Carbon estimates, which attempt to quantify the economic damage of CO₂ emissions, are highly sensitive to their underlying assumptions and so provide limited independent information.

The report supports a more nuanced and evidence-based approach to climate policy. The risks and benefits of a climate changing under both natural and human influences must be weighed against the costs, efficacy, and collateral impacts of any "climate action", taking into account the nation's need for reliable and affordable energy with minimal local pollution. Assumptions about future emissions should be grounded in reality. Climate models should be re-evaluated to address biases and uncertainties, and the limitations of event attribution studies should be clearly acknowledged. An approach that acknowledges both the potential risks and benefits of CO₂, rather than relying on flawed models and extreme scenarios, is essential for informed and effective decision-making.

INTRODUCTION: OVERVIEW AND PURPOSE OF THIS DOCUMENT

This document originated in late March 2025 when Secretary Wright assembled an independent group to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the US public. We agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The group began working in early April with a deadline of May 28. The short timeline and the technical nature of the material meant that we could not comprehensively review all topics. While the report is intended to be accessible for non-experts, we have omitted some introductory or explanatory material that can easily be accessed elsewhere. Nor have we attempted to survey entire literatures related to the topics covered. We have focused as much as possible on literature published since 2020 and referenced previous IPCC and NCA assessment reports. We have also used data through 2024 where possible.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support of independent scientific assessment.

May 2025

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PART I: DIRECT HUMAN INFLUENCE ON ECOSYSTEMS AND THE CLIMATE

1 CARBON DIOXIDE AS A POLLUTANT

Chapter summary

Carbon dioxide (CO₂) differs in many ways from the so-called Criteria Air Pollutants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

The Clean Air Act of 1970 defined six so-called Criteria Air Contaminants subject to regulation (EPA): particulate matter, ground-level Ozone, Sulfur Dioxide, Nitrogen Dioxide, Lead and Carbon Monoxide (CO). In 2007, the Supreme Court ruled that greenhouse gases (CO₂ among them) were also “pollutants” subject to regulation under Clean Air Act (*Mass. v. EPA*, 2007). While the definition of “pollutant” is ultimately a legal one, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are beneficial for vegetation. In these aspects, CO₂ is similar to water vapor.

Ambient outdoor air today contains about 430 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The US Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA, 2024). Allen et al. (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG) that alters the earth’s energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

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2 DIRECT IMPACTS OF CO₂ ON THE ENVIRONMENT

Chapter summary

CO₂ enhances photosynthesis and improves plant water use efficiency, thereby promoting plant growth. Global greening due to increased CO₂ levels in the atmosphere is well-established on all continents.

CO₂ absorption in sea water reduces the alkalinity of the oceans. The recent decline in alkalinity is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Declining alkalinity might adversely affect corals, although the Australian Great Barrier Reef has shown considerable growth in recent years.

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4% and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

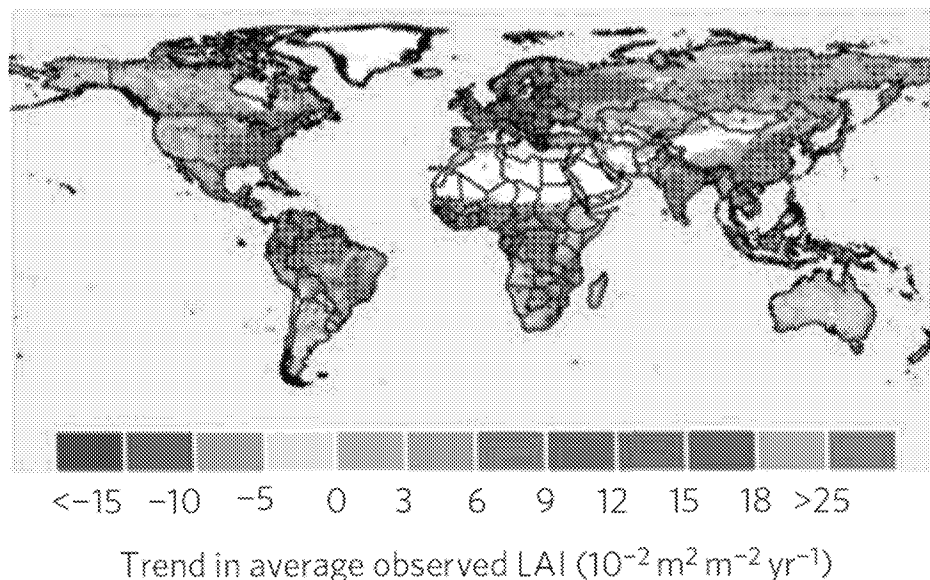


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it through land management changes. Thus, while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increased in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.1.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

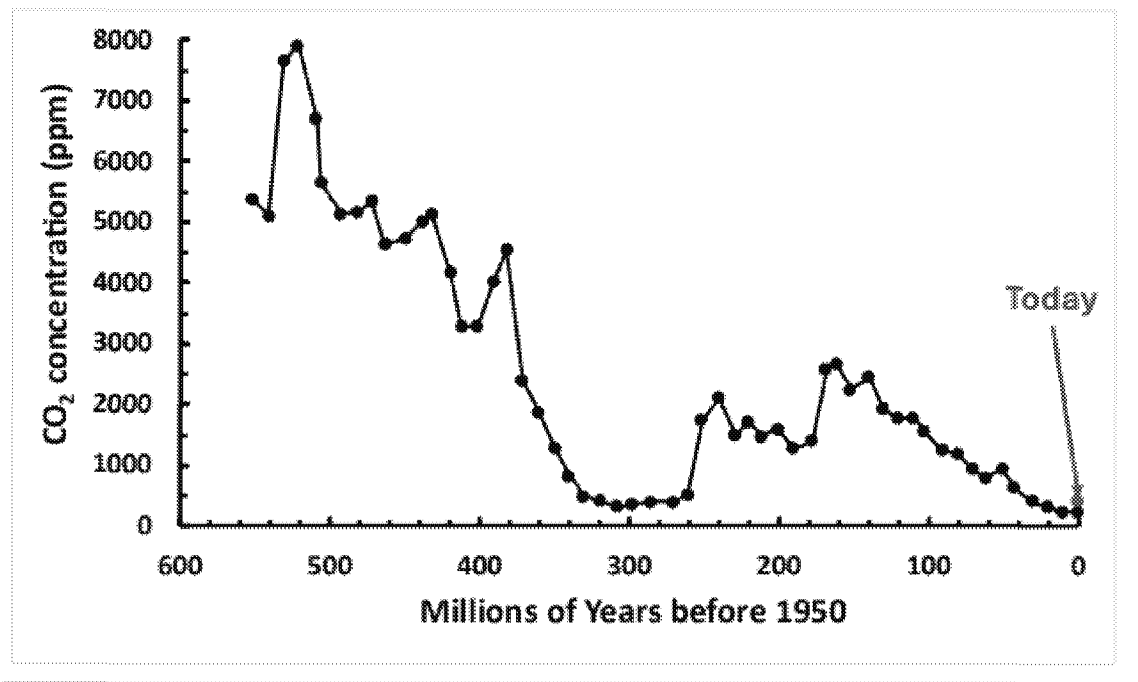


Figure 2.2. Ambient CO₂ levels over the past 550 million years. Today's concentration of 430 ppm is also shown. Source: (Berner 2006)

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C₄, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C₃ process to function more efficiently. For agricultural purposes the plant categories are:

- C₃: rice, wheat, soybeans and most other crops
- C₄: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C₃ species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C₃ plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C₄ plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

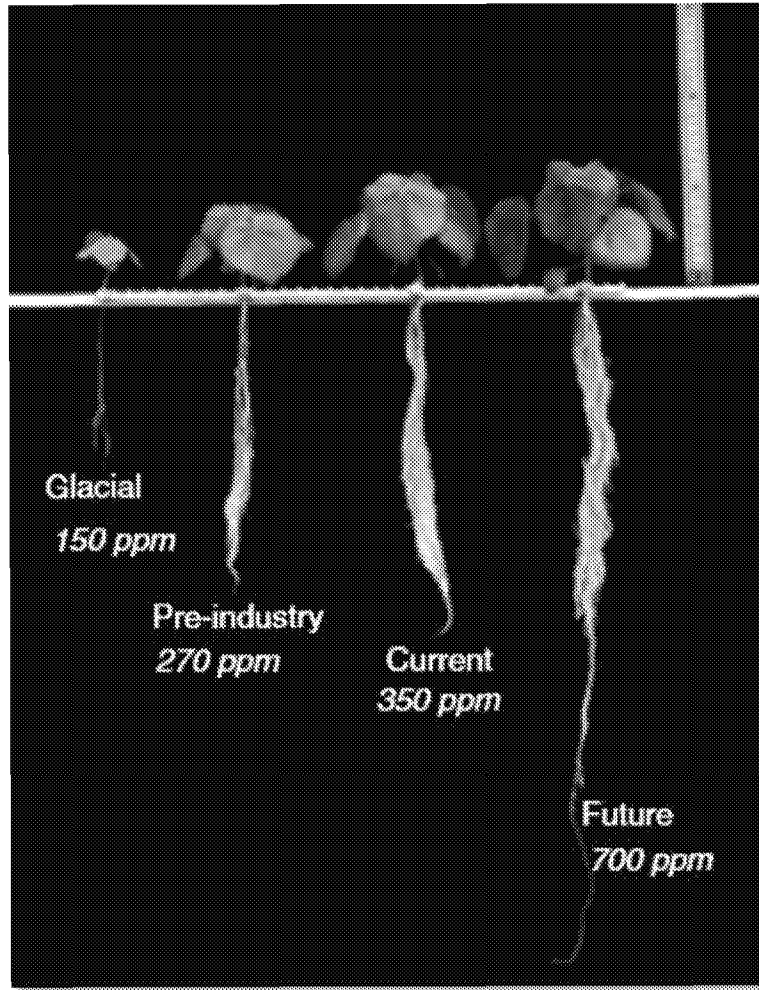


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010). Note “Current” refers to 2010 in image.

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 CO₂ fertilization benefits in IPCC Reports

The IPCC has only minimally discussed global greening and CO₂ fertilization of agricultural crops. The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

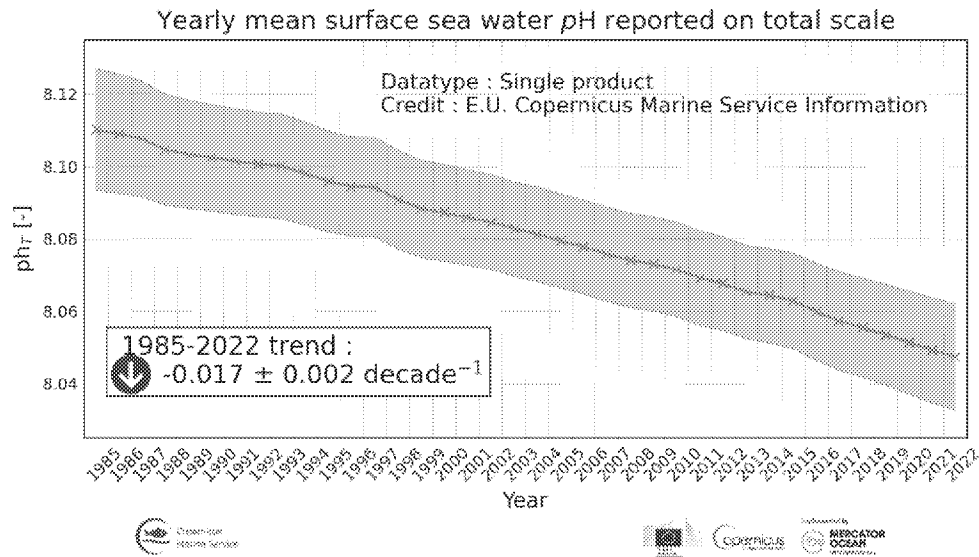


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De’ath et al. (2009) reported that a portion of Australia’s Great Barrier Reef (GBR, the world’s largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole, 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

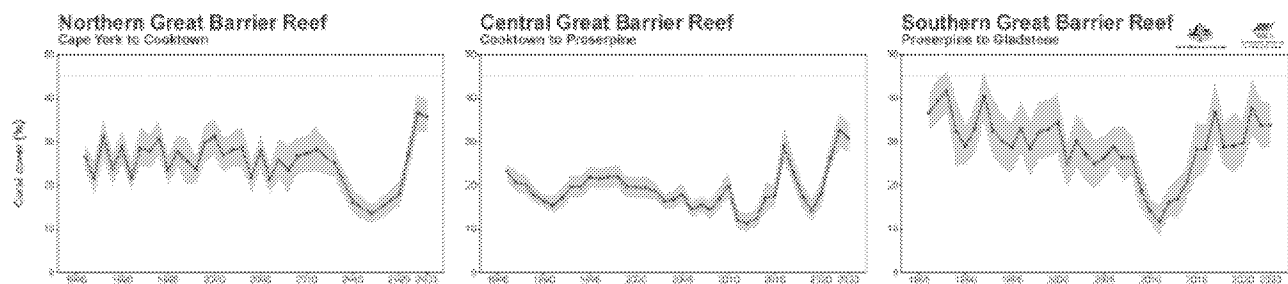


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016).

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research (Clements et al., 2022).

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

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3 HUMAN INFLUENCES ON THE CLIMATE

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. The vast majority of academic climate “impacts” studies in recent years are based upon the extreme 8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. Models disagree over the rate of land and ocean CO₂ uptake but all agree that it has been increasing since 1959.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth’s 4.6-billion-year history. The Earth’s temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the radiative heat it emits to space. Averaged over the Earth’s surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth’s energy balance at the top of the atmosphere are quantified by “radiative forcing”, the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC’s estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

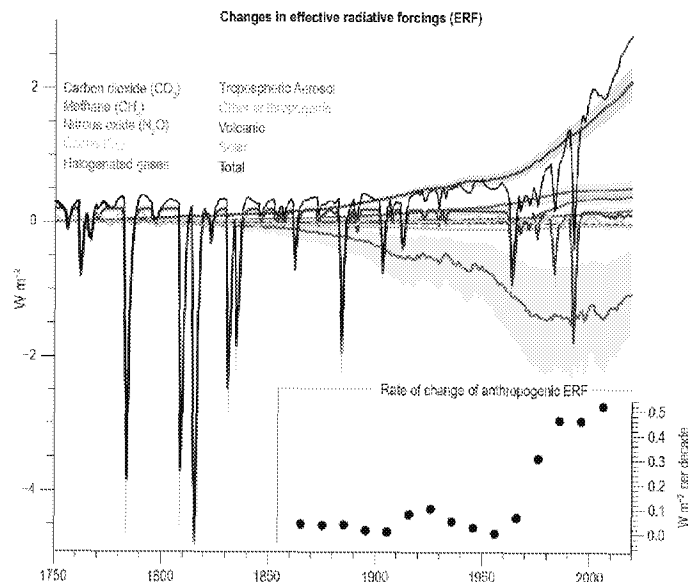


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: [[HYPERLINK "https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/"](https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/)]

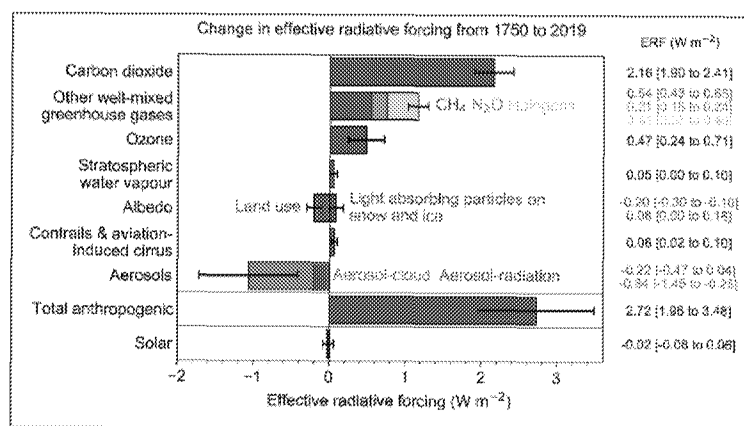


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: [[HYPERLINK "https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/"](https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/)]

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of energy systems. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th Century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta et al. 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the ACRIM data gap is filled. Connolly et al. (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins et al. 2023, Schoeberl et al. 2024).

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- *i.e.*, its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at [[HYPERLINK "https://gml.noaa.gov/ccgg/trends/index.html"](https://gml.noaa.gov/ccgg/trends/index.html)]. The concentration was about 316 ppm at the start of the record in 1959 and is now about 430 ppm, a 36 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

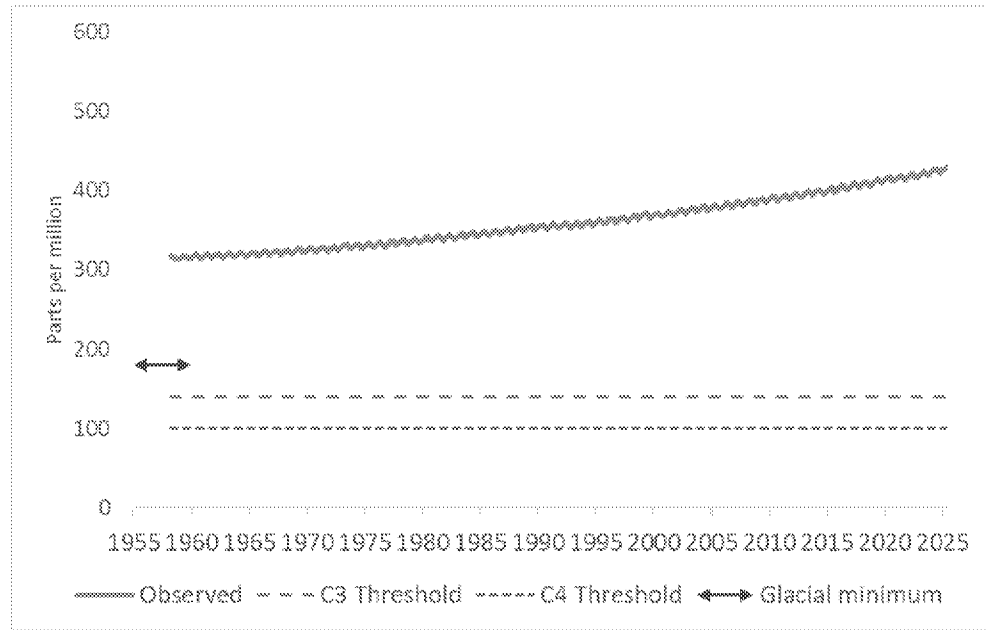


Fig. 3.1.3. CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: [[HYPERLINK "https://gml.noaa.gov/ccgg/trends/index.html"](https://gml.noaa.gov/ccgg/trends/index.html)]

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb “excess” CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If they are not removed the data may over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures suffice for the purpose.

AR6 downplayed the issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10% in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10% upper bound without citing a source. AR4 (WGI p. 244) cited Jones et al. (1990) and Peterson et al. (1999) as the basis of the claim. Peterson et al. had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons and the relative influence of urbanization begins well below that (Spencer et al., 2025). Jones et al. compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of “rural” included towns of up to 10,000 in the

former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10% in these areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10% of the observed warming trend.

Prior to the IPCC AR4 several papers appeared in print arguing that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. The claim attracted controversy because it was presented with no supporting evidence. McKittrick (2010) ++and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. The AR5 (p. 189) conceded that the AR4 had provided “no explicit evidence” for its assessment and further acknowledged, based on these papers, that there was “significant evidence for such contamination of the record” i.e. a warming bias in the land record. However as noted, elsewhere in the report they carried forward the AR4 claim that it was less than 10% of observed warming and they expressed no caution against using the land record for climate measurement on the assumption that it is not contaminated with UHI bias. Recently Soon et al. (2023) estimated an urbanization bias in the Northern Hemisphere land record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

Some studies providing evidence against UHI contamination compared warming rates between rural and urban locations (Jones et al. 1990, Peterson et al. 1999, Wickham et al. 2013). It is not known whether such methods would be capable of detecting UHI bias even when present. The influence of UHI warming is logarithmic, in other words it is strongest at low population growth levels then tapers off as local urbanization expands (Oke 1973, Spencer et al. 2025). Hence finding the same or more warming in rural areas than in nearby urban areas is consistent either with UHI bias being absent or present. McKittrick (2013) provided an empirical demonstration in which the rural/urban trends were not significantly different in a data set shown on other grounds to be contaminated with UHI bias.

Parker (2006) instead examined a sample of urban locations and found no difference in trends between subsets partitioned according to nighttime wind speed, concluding on this basis that urbanization could not be a significant factor. Here again the question is whether such a method would find UHI bias even if present. McKittrick (2013) presented an example in which UHI-contaminated data did not exhibit significant trend differences when stratified according to wind speed.

The challenge in measuring UHI bias is relating local temperature change to a corresponding change in population or urbanization, rather than to a static classification variable such as rural or urban. Spencer et al. (2025) use newly-available historical population archives to undertake such an analyses and found evidence of significant UHI bias in US summertime temperature data.

In summary while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases are not removed by the data processing algorithms used to produce climate data sets.

3.3 Future emission scenarios and the carbon cycle

3.3.1 Emission scenarios

Because of the great uncertainties about these many factors in the decades to come, Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic

activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SREP scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SREP scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

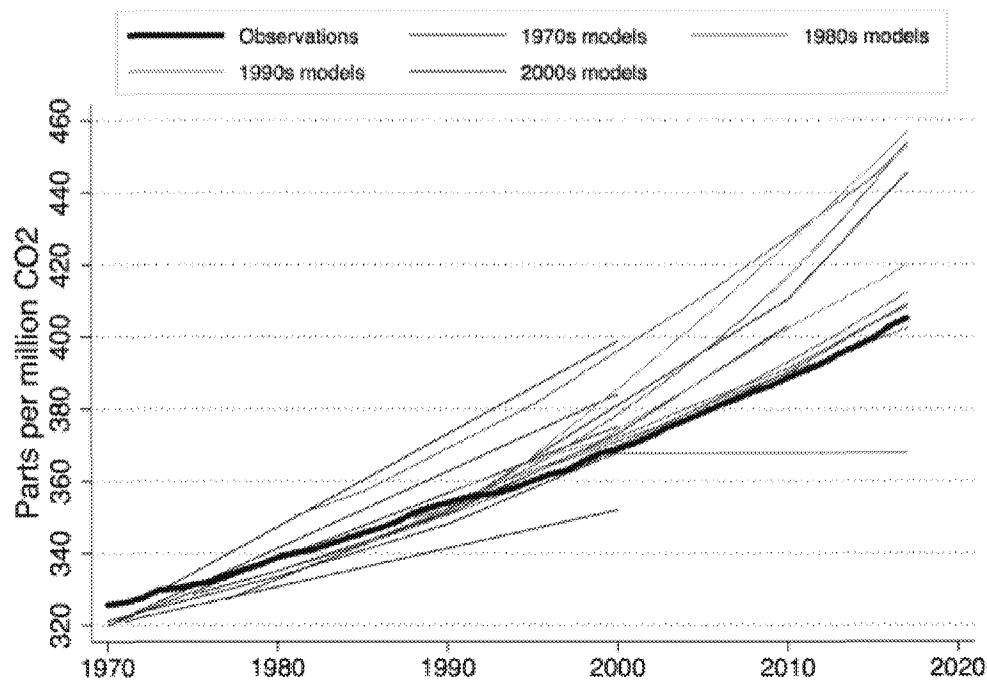


Figure 3.3.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather *et al.* (2019) Figure S4.

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.3.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

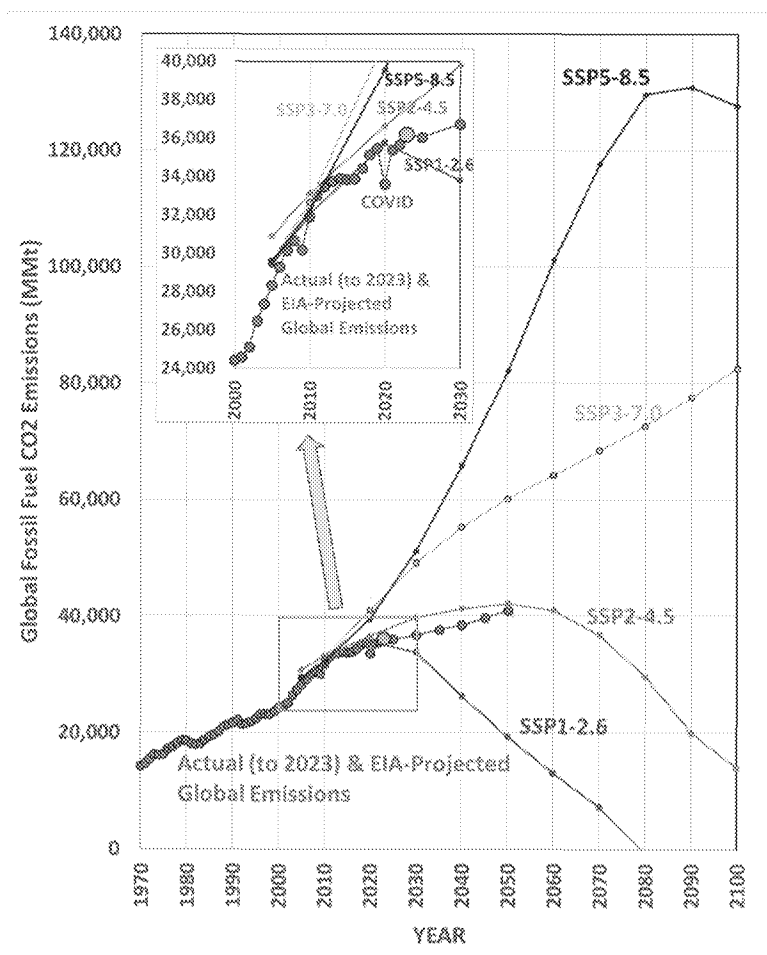


Figure 3.3.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5. Data source: Friedlingstein et al. (2024).

3.3.2 The carbon cycle relating emissions and concentrations

Carbon dioxide emissions from fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) have led to steadily increasing CO₂ concentrations in the atmosphere, as shown in Fig. 3.1.3. The relation between emissions and concentration is determined by the global carbon cycle of land and ocean processes that exchange carbon with the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021).

There are about 850 Gt of carbon (GtC) in the Earth's atmosphere², almost all of it in the form of CO₂. Each year, biological processes (plant growth and decay) and physical processes (ocean absorption and outgassing) exchange about 200 GtC of that carbon with the Earth's surface (roughly 80 GtC with the land and 120 GtC with the oceans). Before human activities became significant, removals from the atmosphere

² Because CO₂ is chemically transformed through the course of the carbon cycle, it is more convenient to track atoms of carbon rather than molecules of CO₂. One gigatonne of carbon (GtC) is equivalent to about 3.7 Gt of CO₂.

were roughly in balance with additions. But burning fossil fuels (coal, oil, and gas) takes carbon out of the ground and adds it to the annual exchange. That addition (together with a much smaller contribution from cement manufacturing) amounted to 10.3 GtC in 2023, or only about 5 percent of the annual exchange.

The carbon cycle accommodates about 50 percent of humanity’s small annual injection of carbon into the air by naturally sequestering it through plant growth and oceanic uptake, while the remainder accumulates in the atmosphere (Ciais et al., 2013). For that reason, the annual increase in atmospheric CO₂ concentration averages only about half of that naively expected from human emissions.

To project future CO₂ concentrations in the atmosphere, and hence future human influences on the climate, it is important to know how the carbon cycle might change in the future. The historical near-constancy of that 50% fraction means that the more CO₂ humanity has produced, the faster nature removed it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in the 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp *et al.* (2021).

CO₂ uptake by land processes

The uptake of extra CO₂ from the atmosphere by land surface processes (as also inferred from global greening) has been modeled with 20 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). As seen in Fig. 3.3.3, all of those models agree that vegetation and soils have been sequestering carbon from the atmosphere. But we also see that the long-term trends over 1959 to 2023 (65 years) vary widely between models, by nearly a factor of 7. This demonstrates that there remains considerable uncertainty regarding how fast CO₂ from the atmosphere is being removed by land processes, which in turn translates into uncertainty regarding future atmospheric CO₂ concentrations. Those uncertain future CO₂ concentrations then imply a source of uncertainty in climate model simulations of future climate change.

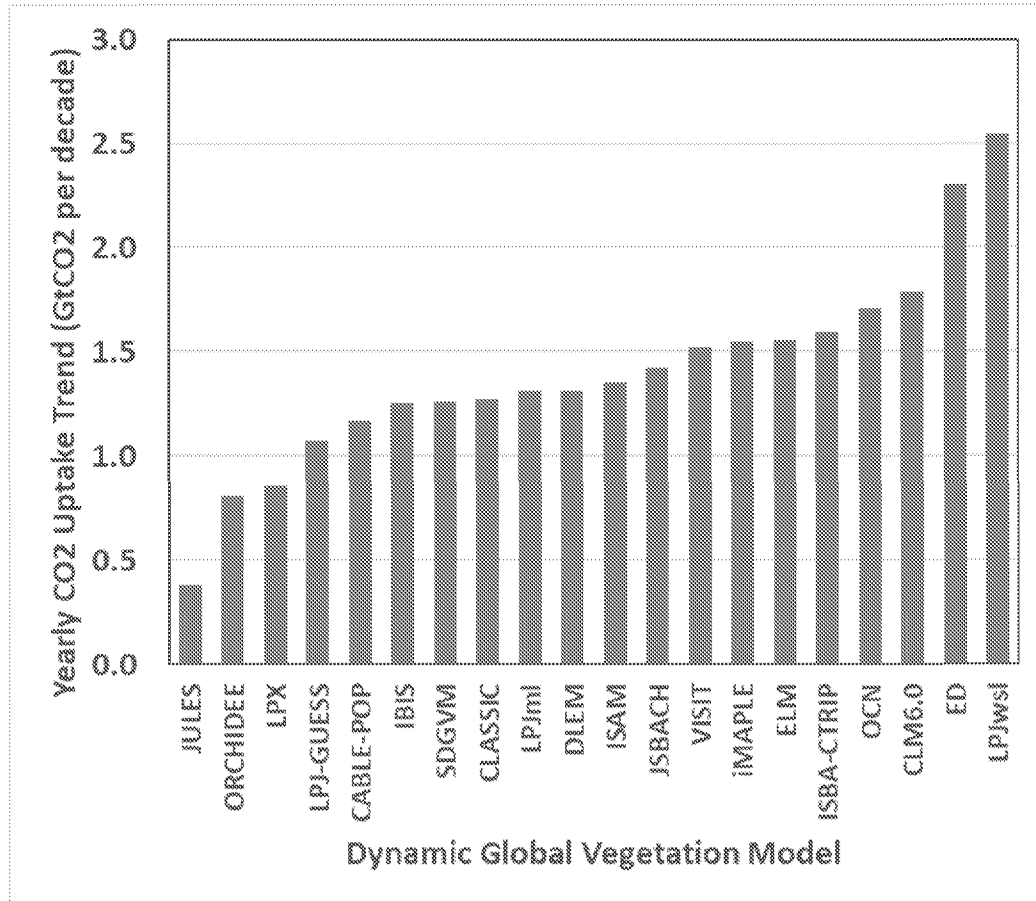


Figure 3.3.3 Decadal trends in the yearly CO₂ uptake by land processes during 1959-2023 simulated by 20 different dynamic global vegetation models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

CO₂ uptake by ocean processes

The uptake of extra CO₂ from the atmosphere by ocean processes has been modeled with 10 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). Like the results from the land models, all of the ocean models agree that the global oceans have been sequestering carbon from the atmosphere at an increasing rate during 1959-2023 (Fig. 3.3.4). Unlike the land models, however, the ocean models show much better agreement with each other, with the model producing the fastest increasing CO₂ uptake being only 65% faster than the model with the most slowly increasing CO₂ uptake. Note that the average trend in CO₂ uptake across all land models in Fig. 3.3.3 is 25% larger than the average trend in ocean uptake. This suggests land processes are increasing in their ability to remove CO₂ faster than ocean processes are increasing their CO₂ sequestration.

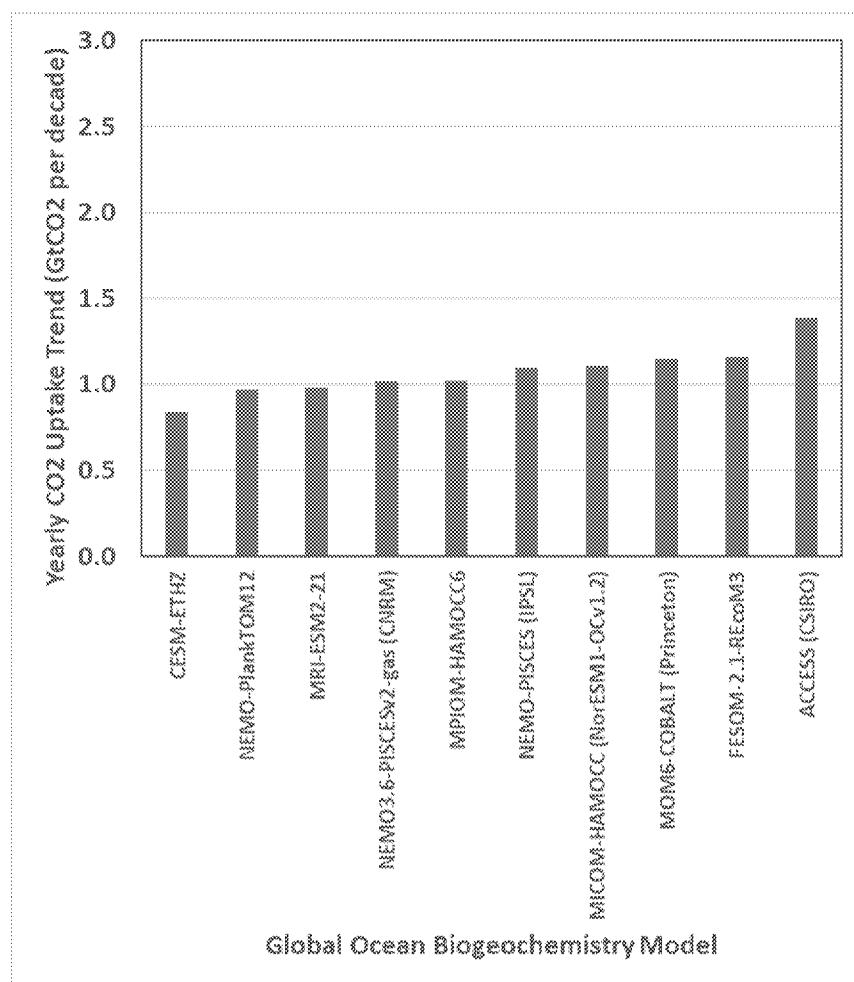


Figure 3.3.5 Decadal trends in the yearly CO₂ uptake by ocean processes during 1959-2023 simulated by 10 different ocean biogeochemistry models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

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PART II: CLIMATE RESPONSE TO CO₂ EMISSIONS

4 CLIMATE SENSITIVITY TO CO₂ FORCING

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches using historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is more weakly justified. Evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on “climate action.” The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the US National Academy of Sciences (Charney *et al.* 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5–4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it. Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0–5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behaviour of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth's climate sensitivity.

ECS is an emergent property of climate models—that is, it is not directly parameterized or tuned. Historically, collections of parameterizations have been chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes, particularly in AR4 and to a lesser extent in AR5. Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model’s climate sensitivity being outside an accepted range. For example, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks, whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in the AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in the AR6 to between 1.8 and 5.7°C (Chen et al., 2021, Scaffeta 2021, see Figure 5.1). Far from settling the model-based sensitivity of climate system uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

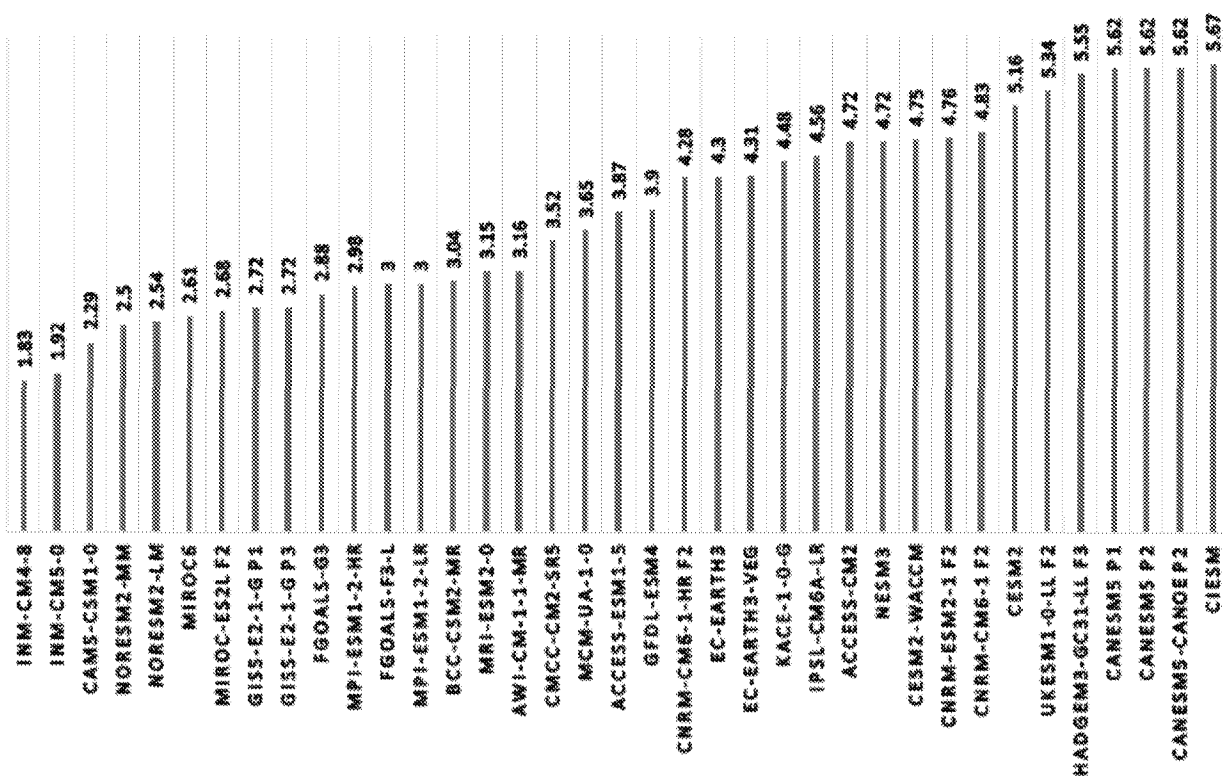


Figure 4.1 Equilibrium Climate Sensitivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021) <https://www.mdpi.com/2225-1154/9/11/161>

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6(2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods, chiefly a recent empirical estimate.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al., 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis, 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth’s temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis’ analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster et al., 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentrate where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

4.4 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the amount of warming that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (i.e., doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS.

IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 6, a real-world ECS smaller than the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Section 8), where model responses need to be downscaled to align with observed trends.

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5 MODELS VERSUS OBSERVATIONS IN THE RECENT PAST

Chapter summary

Climate models show warming biases in many aspects of their reproduction of the past few decades. In response to observed changes in forcing inputs they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

Climate models also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The IPCC has acknowledged some of these issues but not all.

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. To assess the fitness of climate models for this purpose, it is reasonable to ask how well they reproduce the current climate and its variations over the past century. The nearby box “Climate modeling” gives some detail on how climate models work.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three, as we discussed in the previous chapter. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

Box: Climate modeling

Most climate models, except for the simplest ones, represent Earth's land surface using a grid of squares, typically 100 km wide. To simulate the atmosphere, 10 to 20 layers of grid boxes are stacked above these squares. The ocean is modeled using a similar but finer grid, resulting in approximately one million grid boxes for the atmosphere and 100 million for the ocean.

The computer models, based on physical laws, calculate how air, water, and energy move between grid boxes over time. The time step can be as small as 10 minutes, and repeating this process millions of times allows the simulation of climate over centuries. Running these models, even on the most powerful supercomputers, can take months. Comparing simulation results with historical climate data helps assess the accuracy of a model, while projections into the future estimate climate changes under assumed human and natural influences.

Despite sounding straightforward, climate modeling is highly complex. Many critical processes occur at scales smaller than the 100 km grid size. For instance, the flows of sunlight and heat in the atmosphere depend strongly on cloud cover. Since tracking individual clouds is impractical, researchers must make "subgrid" assumptions about the distribution of clouds in each grid box. Snow and ice cover, which affects how much sunlight is reflected or absorbed by the surface, is another subgrid factor.

Each subgrid assumption requires numerical parameters, which must be carefully set. Modelers initially estimate these parameters based on physics and observed climate patterns, then run the model. Because early results often diverge significantly from real-world observations, they "tune" these parameters to better match observed climate features. Different modeling teams use distinct assumptions and tuning strategies, leading to varied outcomes. Tuning is a necessary but delicate aspect of climate modeling, as it is in any complex system. Poor tuning can result in inaccurate simulations, while excessive tuning risks artificially steering results toward predetermined conclusions.

To distill useful insights from these varied models, climate studies often rely on averaged results from multiple models, forming an "ensemble." The latest UN IPCC assessments use the CMIP6 ensemble, which shows a significant diversity of results. One of the most basic climate indicators—the Earth's average surface temperature—varies by about 3°C across the ensemble, three times greater than observed warming during the 20th century.

Although model success in reproducing some features of today's climate is reassuring, the critical issue for society is how well they predict responses to subtle human influences, such as greenhouse gas emissions, aerosol cooling, and land-use changes. The most crucial aspect models must capture correctly is "feedbacks." These occur when climate changes triggered by greenhouse gases either amplify or suppress further warming. For example, as global temperatures rise, snow and ice melt, reducing Earth's reflectivity. With less reflective surfaces, the planet absorbs more sunlight, leading to additional warming. Other significant feedbacks involve water vapor levels, cloud formation, and atmospheric temperature profiles. Based on ensemble averages, the net effect of all feedbacks is estimated to double or triple the direct warming impact of CO₂.

5.2 Surface warming

A straightforward test of a climate model's validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 5.2 is reproduced from Scaffeta (2023), a peer-reviewed study that groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

The leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

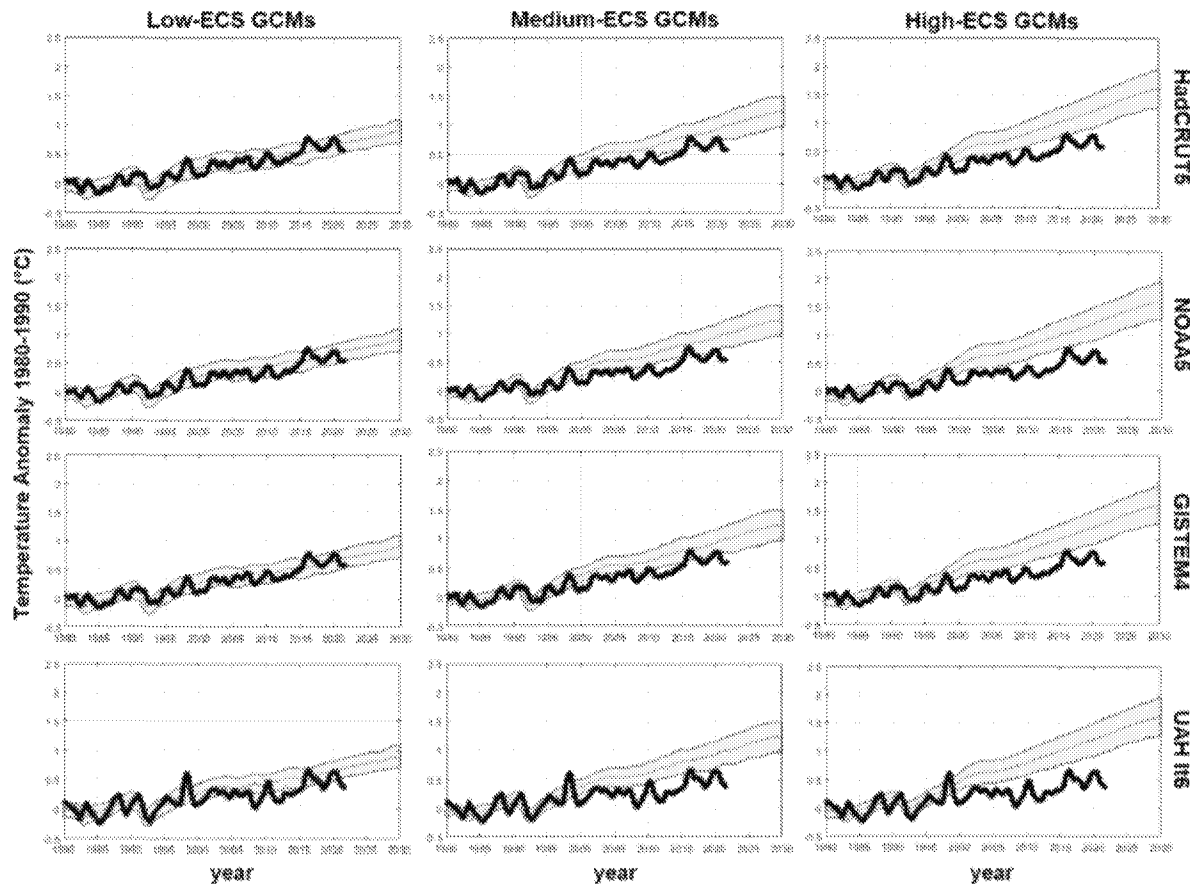


Figure 5.2: model-observational comparisons for Earth’s surface warming. The columns correspond to model groups showing low-ECS to high-ECS, while the rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source. Source: Scafetta N. Climate Dynamics 2023 Fig.2.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by comparing trends in surface temperature data products with those in individual climate models, as summarized in Figure 5.3.

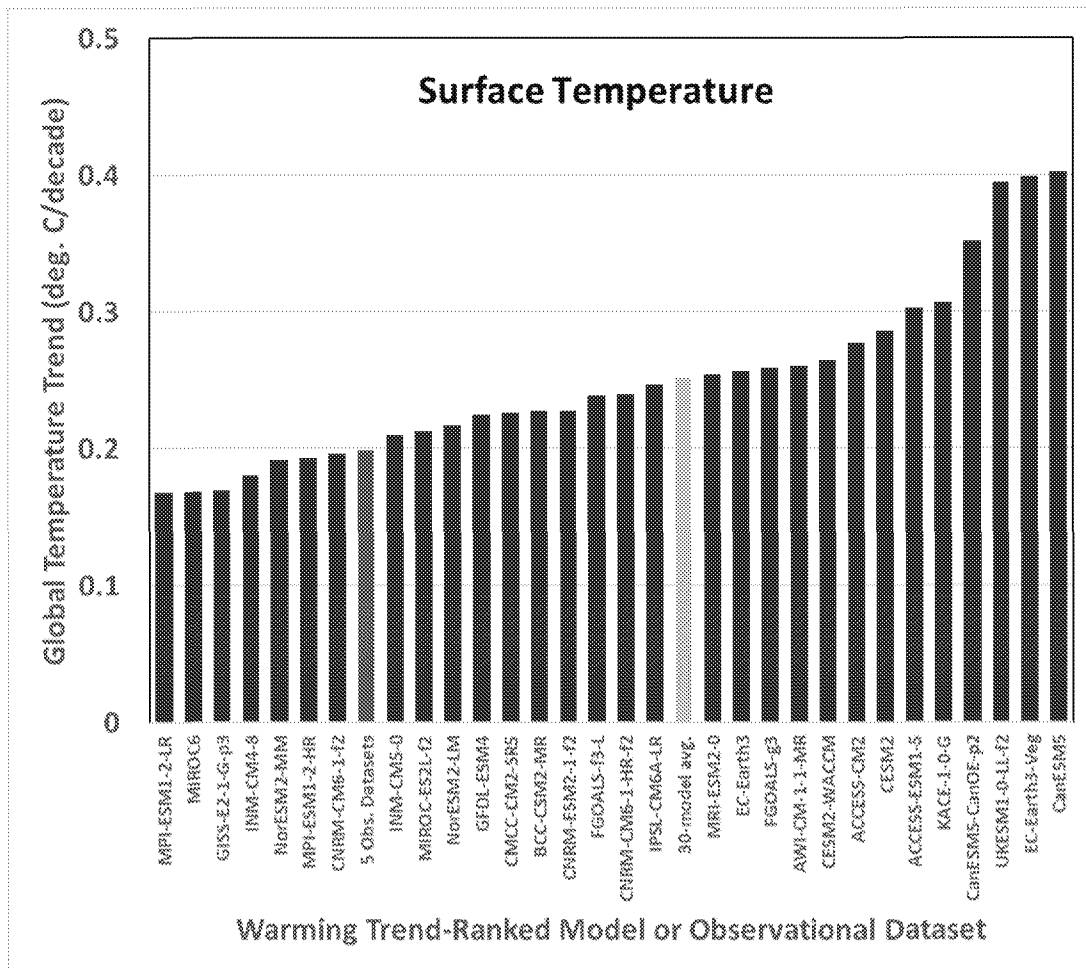


Figure 5.3 Global surface air temperature trends ($^{\circ}\text{C}/\text{decade}$), 1979-2024, from various CMIP6 climate models (red, 30-model average in orange); and the average of three thermometer datasets (HadCRUT5, NOAA Global Temp, and Berkeley 1 deg.) and two reanalysis datasets (ERA5 and NCEP/NCAR R1) in blue.. Source: Spencer (2024) updated

5.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the tropical troposphere. This region is an important test of the models since it has long been hypothesized that this is where the signal of anthropogenic greenhouse warming emerges first and most strongly. Biases in tropospheric trends indicate model flaws in heat transfer processes and carry over to surface warming biases.

The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming trends in CMIP6 climate models to observed trends from satellites, weather balloons and reanalysis systems. Figure 5.4 presents the comparisons with data updated to 2024. Every model overpredicts the average observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics. In most individual models the bias is statistically significant and on average across models it is highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but

even the models with lower average ECS predict too much warming. If future climate models were to realistically represent global tropospheric warming, they would likely be less sensitive than even the low-ECS members of the CMIP6 ensemble

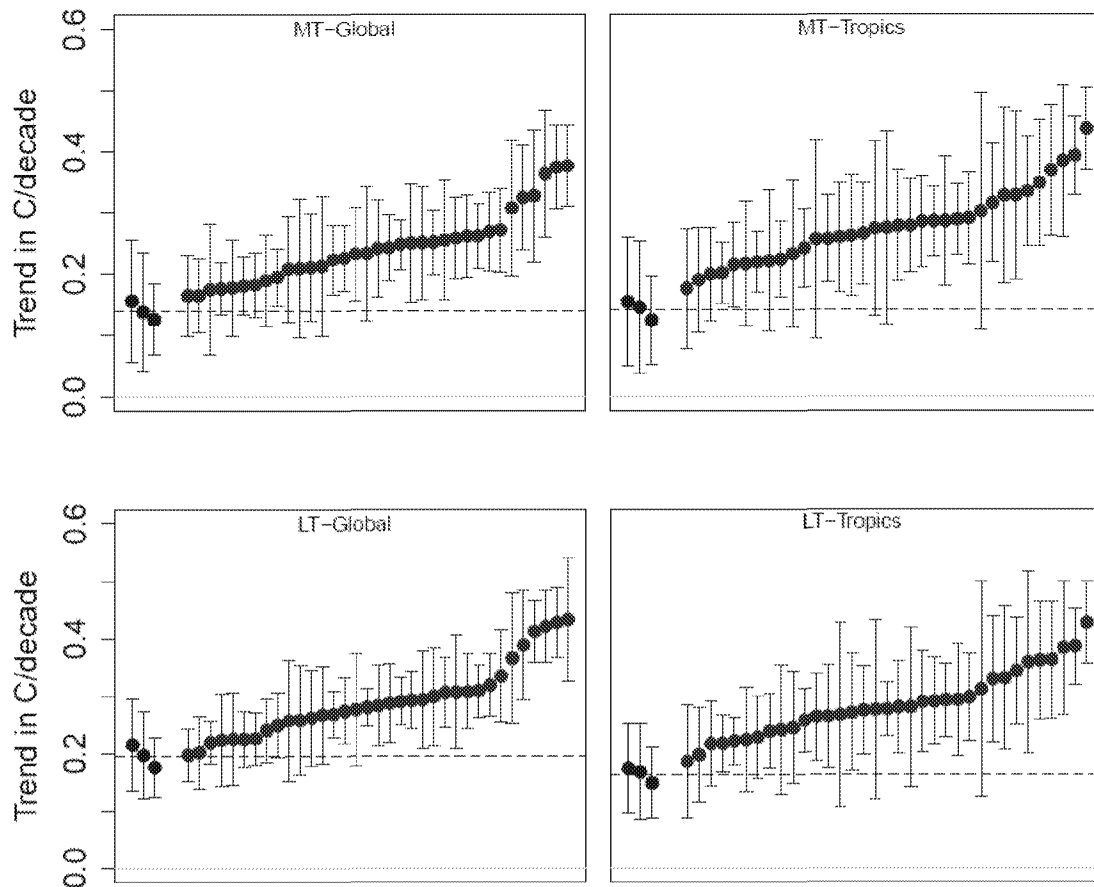


Figure 5.4: Observed versus CMIP6 modeled warming trends ($^{\circ}\text{C}/\text{decade}$ 1979-2024) in the global and tropical lower (LT) and mid-troposphere (MT). Uses methodology of McKittrick and Christy (2020) on updated data. Blue dots: warming trends with 95% confidence interval bars for 3 data products (radiosondes, reanalysis and satellites) and 95% confidence interval bars. Blue dashed line: warming trend average for 3 observed series. Red dots: modeled warming trends in 35 models arranged lowest to highest.

As mentioned the IPCC has long acknowledged the model-observation mismatch. For example AR6 pp. 443-444 offers this on the tropical troposphere (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that

differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5 and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

Notably, despite the accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias.

5.4 Vertical profile mismatch and excess amplification

Another important model-observational discrepancy is the excess amplification with altitude found in climate models. The comparison was in the IPCC AR5 Chapter 10, although only in the online supplement (Figure 10.SM.1) and only in a figure the formatting of which made the point difficult to see. Figure 10.SM.1 is not referenced in the main IPCC report nor in any summary so readers would not have been aware of it. Although not apparent at first glance, it shows that the 1979-2010 warming in the lower troposphere is so small as to be consistent with no GHG forcing at all, and is inconsistent with the model runs that do have GHG forcing. In Figure 5.6 we adapt IPCC AR5 Figure 10.SM.1 to draw out the critical point.

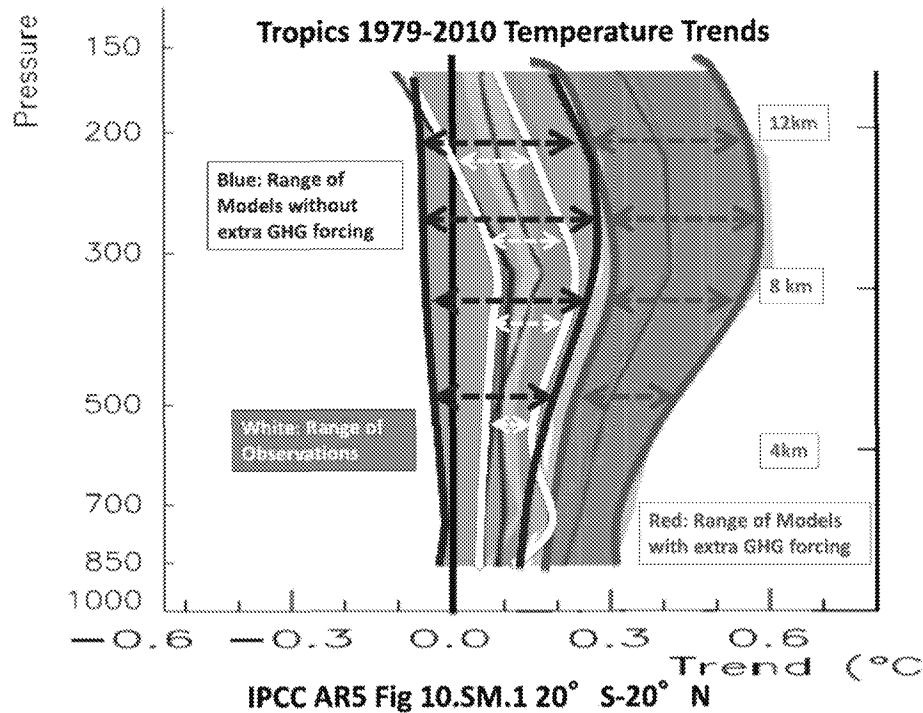


Figure 5.6: Vertical warming pattern for tropics (20S to 20N). Source: Annotated version of IPCC AR5 Figure 10.SM.1

Figure 5.6 compares temperature trends by altitude between models and observations between 20S and 20N (the tropics). In this region where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.7. Modeled temperature trends exceed observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.7 is the tropical tropospheric temperature (TTT) average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

The wide range of choices made by modelers to characterize the physical processes in the models (see Box: Climate Modeling in Section 5.1 above) is seen by the large spread of trends in the middle troposphere where values range over $\pm 40\%$ from the median value (Fig. 5.7). This illustrates the uncertainties characteristic of the varying attempts to model (parameterize) a complex system involving turbulence, moist thermodynamics and energy fluxes over the full range of time and space scales.

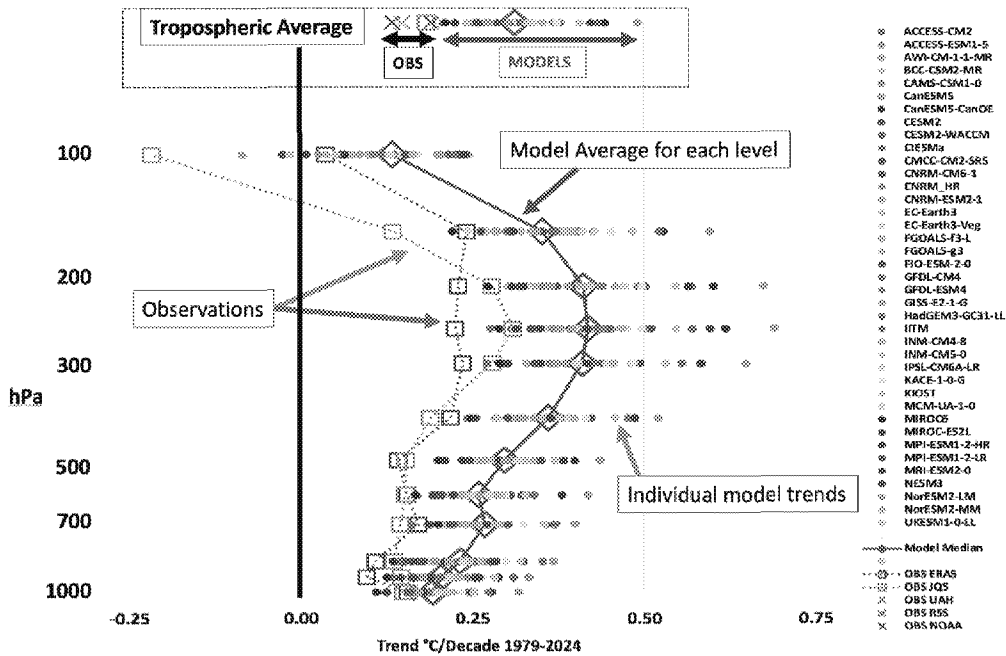


Figure 5.7: Modeled versus observed warming, tropical troposphere. Source: updated from Christy and McNider (2017) including data through 2024. Red line: model average. Green and blue lines: observational series (reanalysis).

This discrepancy has been the source of much controversy, with some arguing that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), showed that models project greater amplification with altitude than is observed. This result was subsequently confirmed by detailed time series analysis (Vogelsang and Nawaz 2016) who found that the model-observational difference is statistically significant.

This is a case in which models are not merely uncertain but share a common bias compared to observations. This suggests the representation of certain fundamental physical processes in climate model feedbacks have large discrepancies not only among models but against the real climate.

The IPCC AR6 did not assess this issue.

5.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to the year 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with **the bulk of the decrease prior to 2000**. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate **models project continued tropospheric warming and stratospheric cooling** over the coming decades. Global average satellite observations of **lower stratospheric temperatures exhibit no significant trends since the turn of the century**. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated **radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.**”

A combination of tropospheric warming and stratospheric cooling is a commonly-cited “fingerprint” of anthropogenic warming. Stratospheric warming since 2000 coincides with continued surface and tropospheric warming, a pattern that is not found in climate model simulations and is not apparently consistent with the anthropogenic fingerprint.

5.6 Snow cover mismatch

Data compiled by the Rutgers University Snow Lab (undated) show that Northern Hemisphere winter snow cover is not decreasing (Figure 5.8). If anything, it shows an increasing trend.

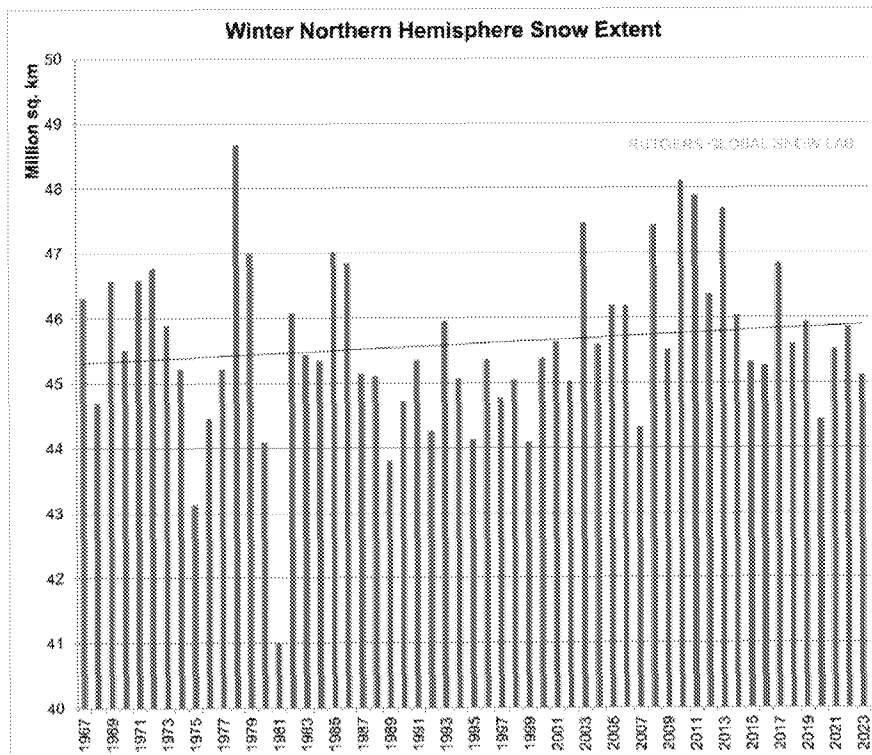


Figure 5.8: Northern Hemisphere Winter Snow extent.

Source: [[HYPERLINK](https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1)

"https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1"] (February 24, 2024)

Yet models project declining Northern Hemisphere snow cover due to climate warming, as described by Connolly et al. (2019).

The climate models were found to poorly explain the observed trends [in Northern Hemisphere snow cover]. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions. Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant.

Connolly et al. (2019).

AR6 largely confines its discussion of changing Northern Hemisphere snow cover extent (SCE) to the Spring season for which models and observations agree on a downward trend. Regarding Winter changes it remarks as follows (AR6 WGI Ch. 2 p. 344):

Assessment of SCE trends in the NH since 1978 indicates that for the October to February period there is substantial uncertainty in trends with the sign dependent on the observational product.

Analysis using the NOAA Climate Data Record shows an increase in October to February SCE (Hernández-Henríquez et al., 2015; Kunkel et al., 2016) while analyses based on satellite borne optical sensors (Hori et al., 2017) or multi-observation products (Mudryk et al., 2020) show a negative trend for all seasons.

AR6 WGI Chapter 9 (p. 1284) points out that the NOAA Climate Data Record showing increased fall and winter SCE is inconsistent with land-based observations and model-based data sets. It notes that using optical satellite imagery to infer SCE in winter is challenging due to cloud cover and decreased solar illumination in winter months.

Focusing on the Pacific Coast states (CA, OR and WA) cold season mountain snowfall that melts in spring and summer provides a substantial portion of warm season water resources. A comprehensive reconstruction of snowfall for the main source regions (Cascades and Sierra Nevada Mountains) indicates no significant trends in annual totals since the late 19th century (Christy 2022).

5.7 Hemispheric symmetry of the planetary albedo

The planetary albedo is the fraction of solar radiation reflected by the Earth back to space, and is an important component of the radiative balance and hence whether the planet will warm or cool over time. An intriguing property of the Earth's albedo is that, on average, the Northern Hemisphere (NH) and Southern Hemisphere (SH) have had very nearly the same albedo at least throughout the fifty-year satellite record (Stephens et al., 2015). This symmetry is surprising, because the SH has much more ocean than land. Since ocean is less reflective than land, the NH should have higher albedo. Clouds (which are highly reflective) are more common in the NH, and so compensate the surface albedo imbalances of the two hemispheres. Datseris and Stephens (2021) show that this cloud compensation comes from the extra-tropical storm tracks of the SH, which are cloudier than those of the NH. While the mechanism for this hemispheric symmetry is unclear, it likely operates on large temporal and spatial scales.

The hemispheric symmetry of the albedo is a simple gross metric for climate models. Rugenstein and Hakuba (2023) defined that metric as the difference between the NH and SH annual mean albedos, expressed as Wm^{-2} of the reflected sunlight, and compiled it for the CMIP6 climate models, as shown in Figure 5.9. Most of the CMIP6 models do not reproduce the small observed asymmetry (about 0.1 Wm^{-2}) and even disagree as to which hemisphere is more reflective. Moreover, the magnitude of the asymmetry ranges up to 5 Wm^{-2} in some models, twice as large as the current anthropogenic forcing (about 2.5 Wm^{-2}).

The significance of unphysical albedo asymmetries in the climate models is not yet fully known. However, other model studies suggest that interhemispheric changes in albedo can alter poleward heat fluxes, meridional temperature gradients, storminess, and differences in hemispheric ocean heat storage. The discrepancy between models and observations further raises issues regarding cloud feedback processes and so more generally diminishes confidence in model projections of the future climate.

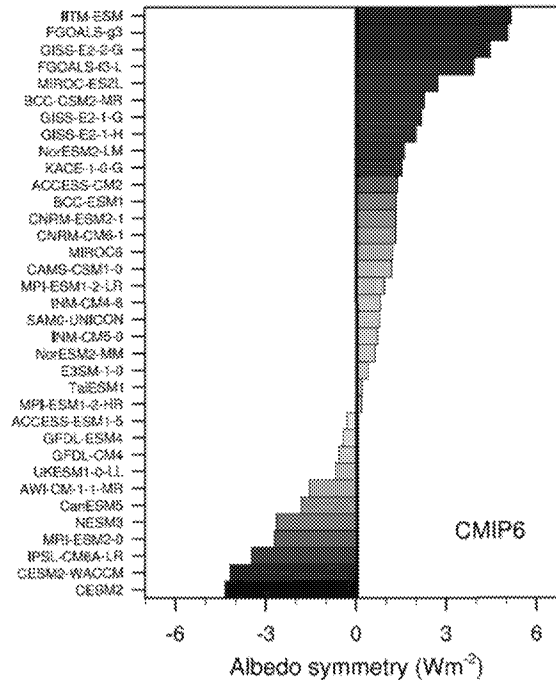


Figure 5.9. Differences in 20-year average reflectivity (albedo) between the Northern and Southern Hemispheres for CMIP6 models used in the most recent IPCC assessment (colored bars). The very small observed difference is indicated by the vertical black line. From Rugenstein and Hakuba (2023).

5.8 US Corn Belt

One of the largest discrepancies between models and observations is in the U.S. Corn Belt, a region of particular importance to global food production. Figure 5.10 shows the warming trends for summertime (June, July, August) for the 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) warm far too rapidly compared to observations (blue).

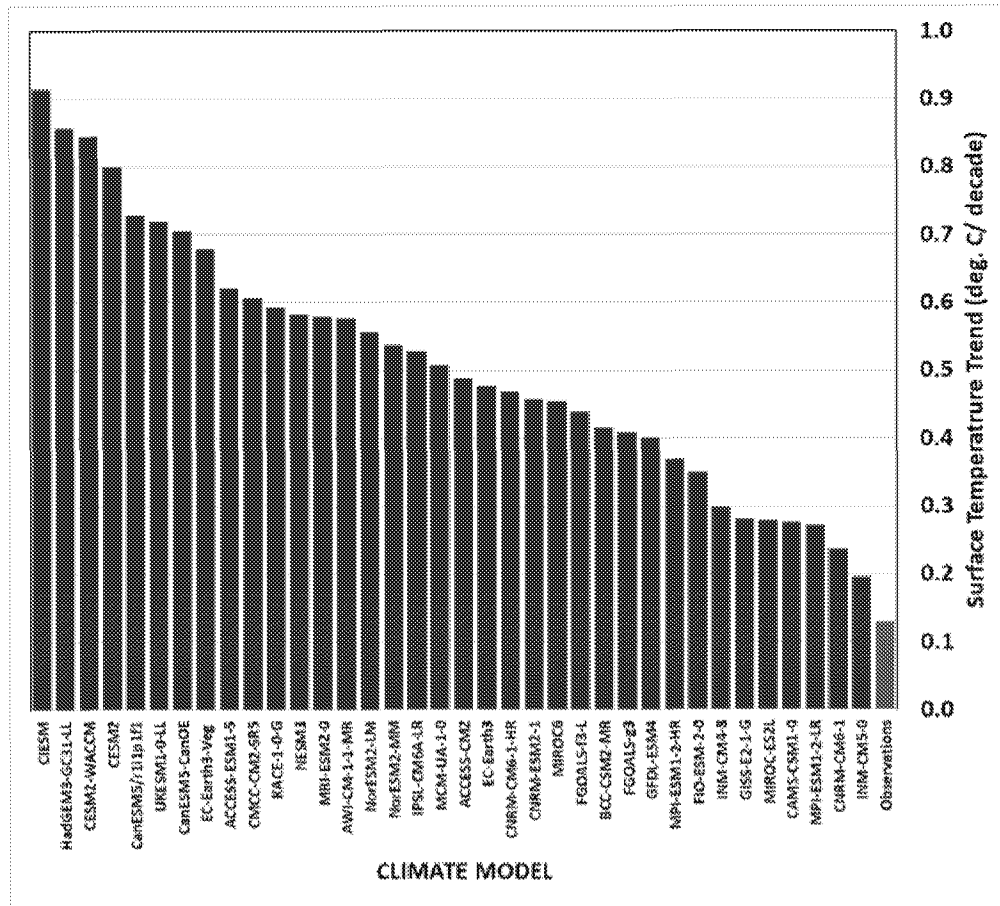


Figure 5.10: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 10, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

The IPCC acknowledges limitations in the accuracy of regional climate model outputs. This example shows that users need to assess model projections carefully on a case-by-case basis since local biases may be sufficiently large that the models are simply not fit for purpose. As has recently been noted by two leaders of the modeling community (emphasis added)

... for many key applications that require regional climate model output or for assessing large-scale changes from smallscale processes, we believe that **the current generation of models is not fit for purpose.** (Palmer and Stevens 2019)

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft

- They also produce too much stratospheric cooling, too much snow loss, and too much warming in the corn belt.
- The hemispheric albedo difference in individual climate models ranges widely in sign and magnitude compared to observations. The range in Watts/m² is three times larger than the direct anthropogenic forcing of CO₂.
- The IPCC has acknowledged some of these issues but not others.

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6 EXTREME WEATHER

Chapter Summary

Most types of extreme weather exhibit no statistically significant long-term trends over the available historical record. While there has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term increases are not detected. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfires are not more common in the US than they were in the 1980s. Burned area increased from the 1960s to the early 2000's however it is low compared to the estimated natural baseline level. US wildfire activity is strongly affected by forest management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or high wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. Climate is about the statistical properties of weather over decades, not single events. And, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed and thus are absent from the databases used to determine extreme statistics [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This chapter is concerned with detection of trends in extreme weather, while Chapter 8 considers causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed, attribution should not be assumed to follow.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition, but it can be thought of as the presence of natural variations with strong autocorrelations that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records that are short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown in Figure 6.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

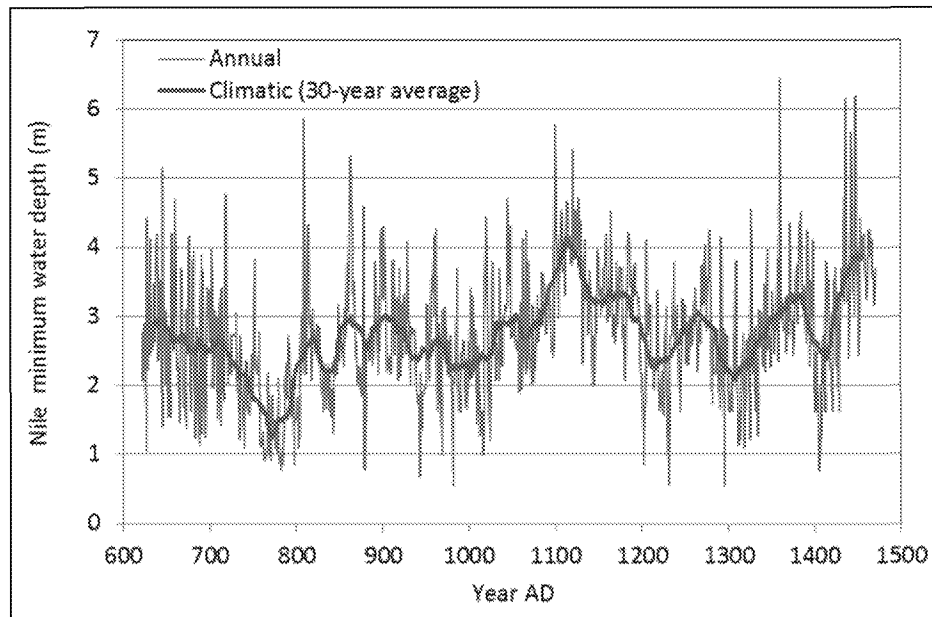


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from ([HYPERLINK "<https://www.itia.ntua.gr/en/docinfo/1351/>"])

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. An emergent theme is the wide gap between public perceptions and scientific evidence. It has become routine in media coverage, government and private sector discussions, and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and “climate change.” Yet expert assessments typically have not drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (2012)

AR6: The IPCC Sixth Assessment Report Working Group 1 (2021).

NCA4: The US Climate Science Special Report of the Fourth National Climate Assessment (2017) Volume I.

NCA5: The US Climate Science Special Report of the Fifth National Climate Assessment (2023) Volume I.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis has been added.

Additionally we present updated data series from standard government sources to provide up-to-date information through 2024 wherever possible.

6.2 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here as a synonym for hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)³

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 6.2.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). There is substantial year-to-year and decadal variability a weak decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes These two trends combine to create an increasing trend in proportion of major hurricanes.

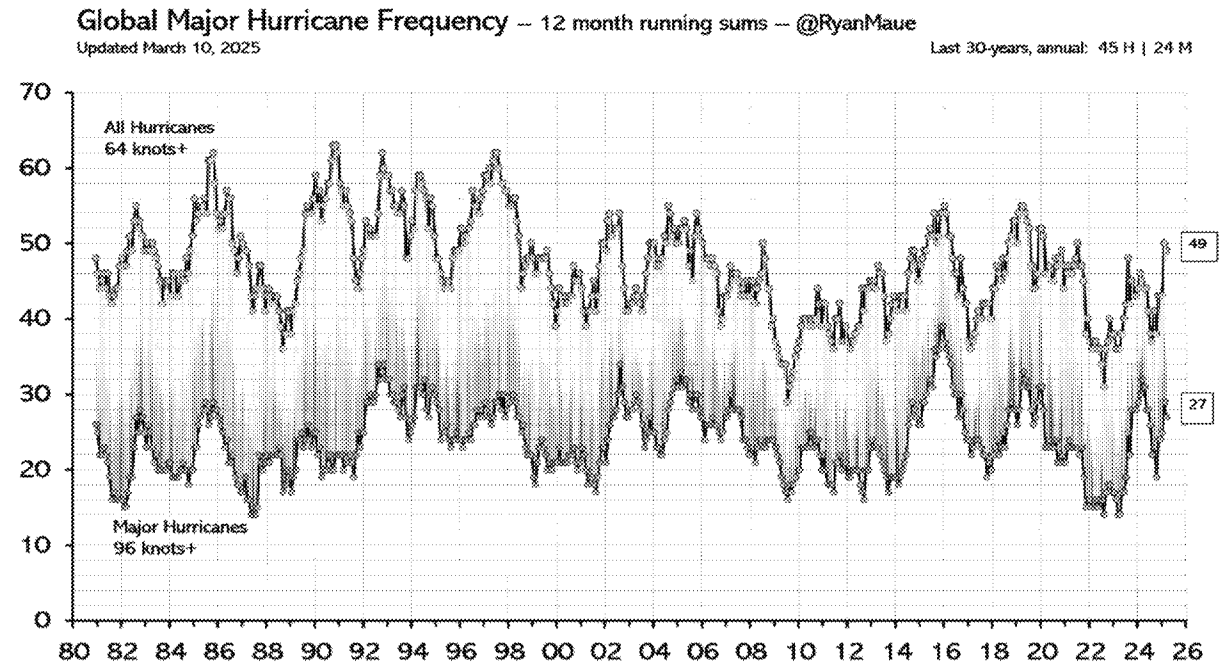


Figure 6.2.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean, which accounts for ~35 percent of total global hurricanes, whereas the Atlantic accounts for ~15 percent of global hurricanes (CSU, 2025). Data in the Atlantic basin extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 6.2.2 shows the frequency of Atlantic hurricanes and major hurricanes (Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (Vecchi and Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

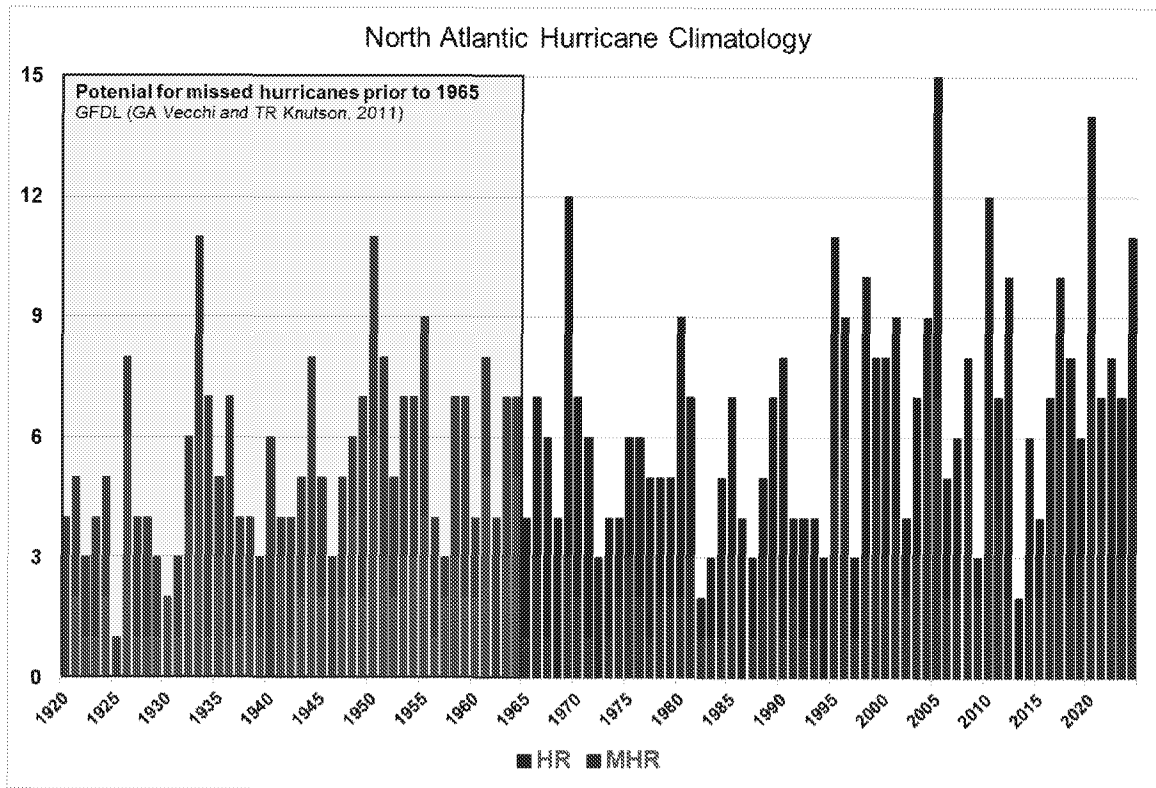


Figure 6.2.2: Atlantic frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source (NHC, 2024)

Figure 6.2.2 shows that Atlantic hurricanes vary strongly on decadal and multidecadal time scales. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is manifest in basin-wide sea surface temperature and sea level pressure fluctuations connected to large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present, but in its cool phase during 1971-1994. The AMO has its greatest impact on the number of major hurricanes (Category 3+), identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear in the AMO warm phase (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.3.3 updates their analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, there is no statistically significant trend since 1920. Figure 6.2.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, there were no major hurricanes striking the U.S from 2006 through 2016, the longest such period since 1920.

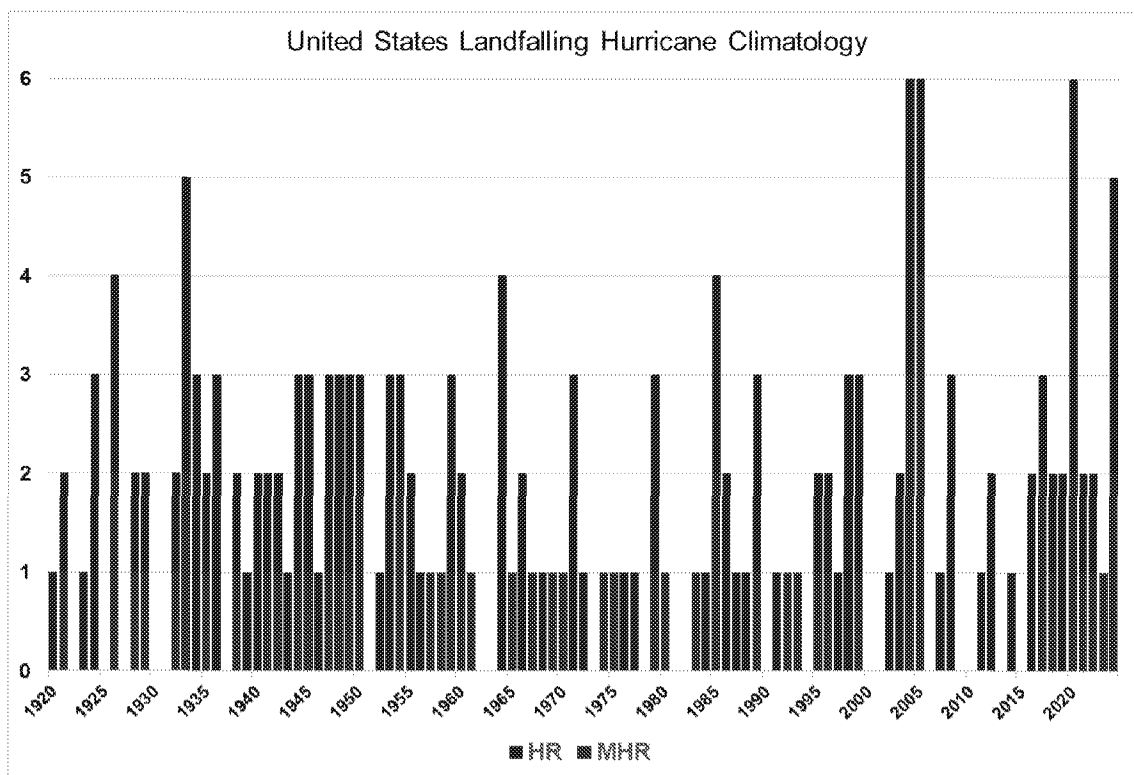


Figure 6.2.3: US landfalling frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 6.2.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, is 1886, with 7 landfalls,

Table 6.2.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation. While it has long been hypothesized that a rising global sea surface temperature would cause an increase in hurricane intensity, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

Table 6.2.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall	Name
		Wind (MPH)	
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

6.3 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. However, the NCA4 noted that heatwave activity in the US reached a peak in the 1930s.

AR6: “It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe” (SPM, A3.1)

AR6: “In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA.” (Chapter 11, p 1550)

NCA4: “Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA4: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, **heat wave magnitude reached a maximum in the 1930s.**” (pp. 190-191)

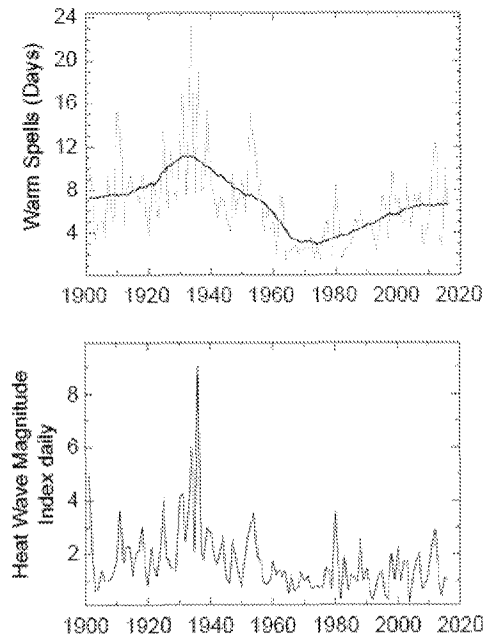


Figure 6.3.1: US Heat waves since 1900. Source: NCA4 Figure 6.4

6.3.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (Tmax, May-Sep) and daily minimum temperatures in the cold season (Tmin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

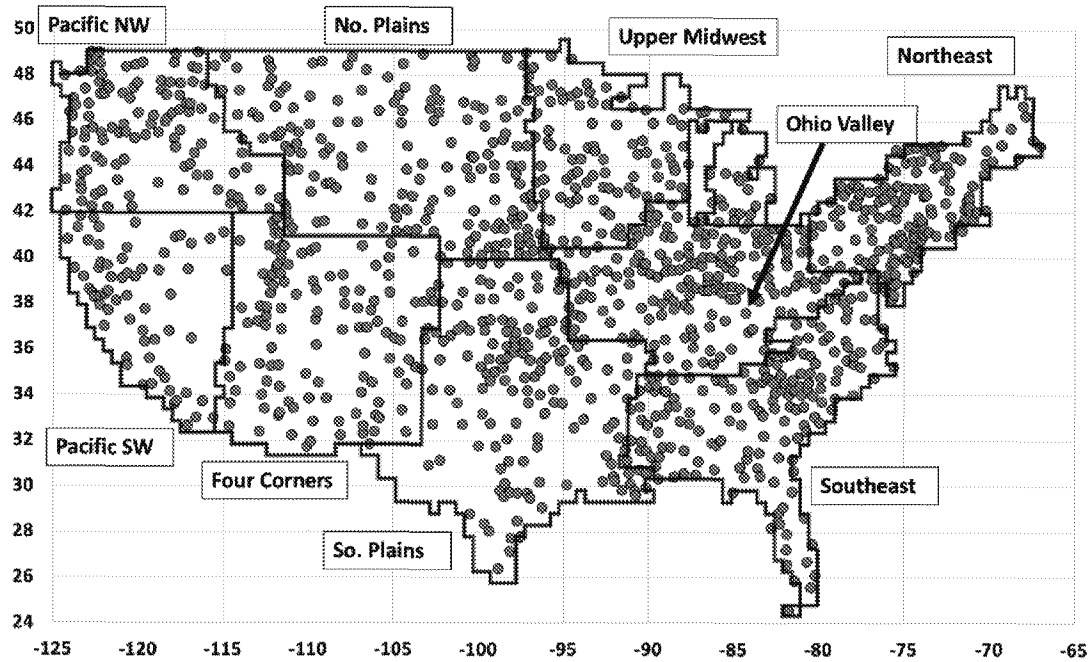


Figure 6.3.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for Tmax would be 1.21 ($=153/126$) per station per year and for Tmin 0.96 ($=122/126$) per station per year.

Figure 6.3.3 shows the observed distribution in time of the occurrence of these extreme events. There is a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the Tmax records and 59% of the Tmin records occurred in the first half of the period (1899-1961).

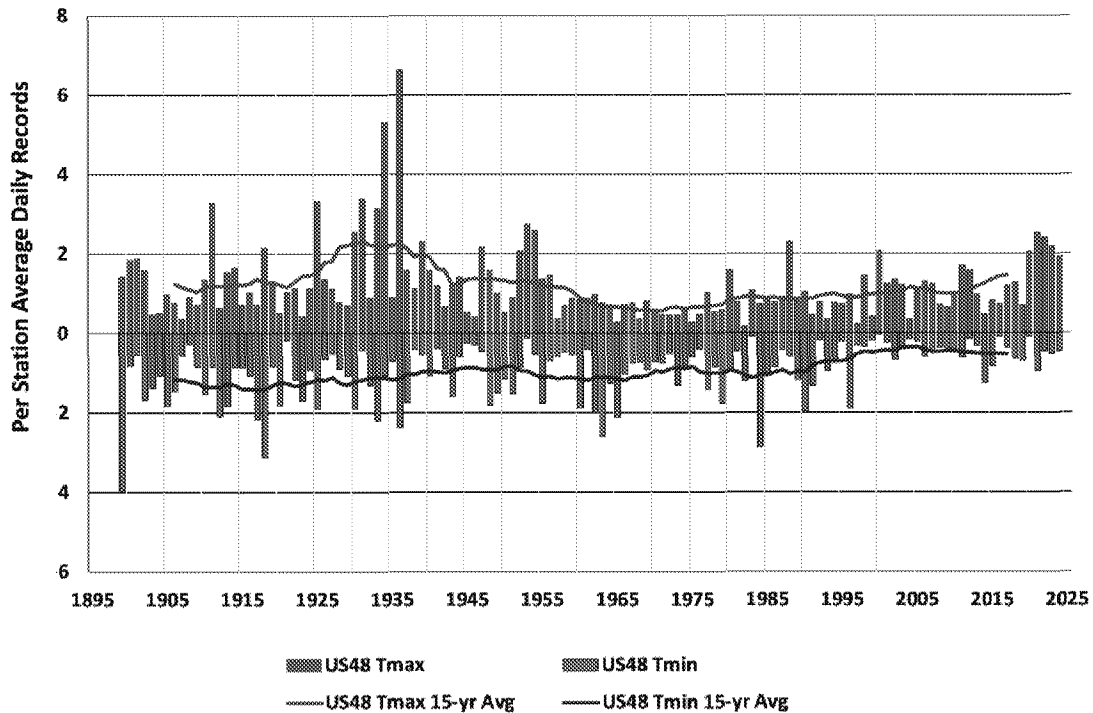


Figure 6.3.3 Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898. US48: contiguous US states. Tmax: maximum temperature. Tmin: minimum temperature.

On the cold side, the Valentine’s Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme Tmax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA4). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.3.4. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.3.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

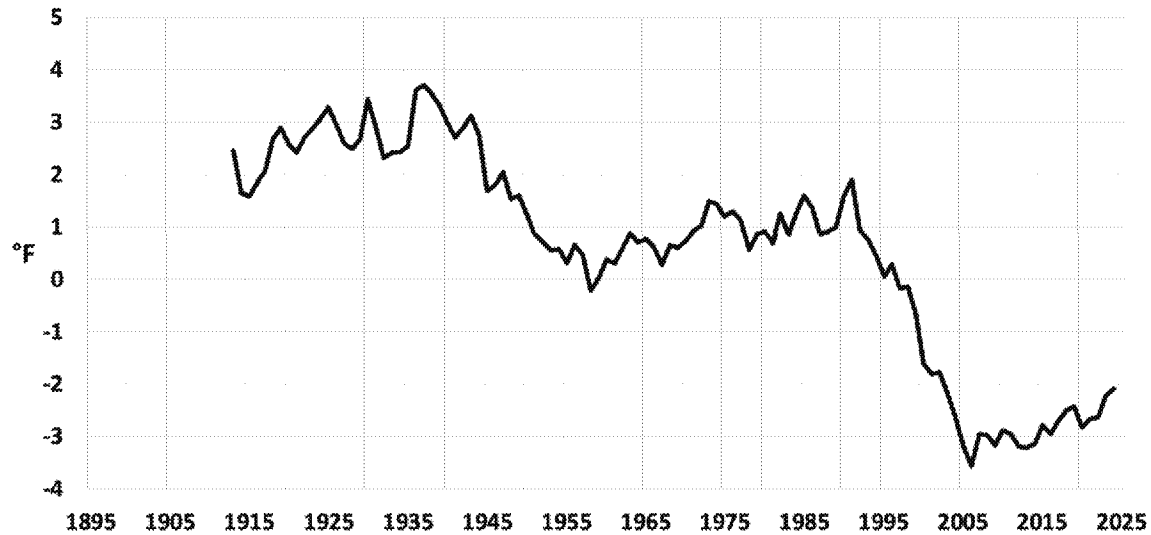


Figure 6.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season Tmax and coldest cold-season Tmin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer Tmax and coldest winter Tmin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter Tmin, but a decline in summer Tmax is also a factor. The rise in Tmin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the U.S. and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured by the range between warm season maxima and cold season minima.

6.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F Tmax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F Tmax temperatures, a small change will not have much impact on the results. In the past 126 years, the average CONUS station

experienced 129 days exceeding 95°C per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, such threshold analyses must be interpreted with caution.

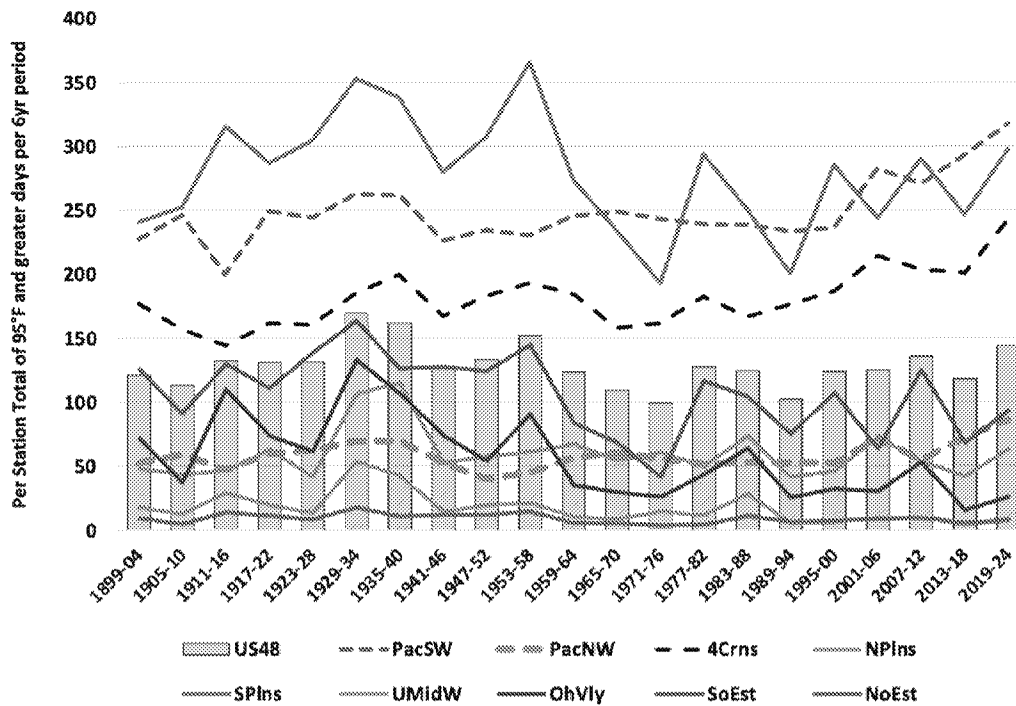


Figure 6.3.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations. US48: contiguous US states. See Figure 6.3.2 for region names.

Figure 6.3.5 shows that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 referenced in the NCA5 quote will be examined more closely in Section 8.5. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.

6.3.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile for that day and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA4, except that the reference period here is the entire record 1899-2024 while NCA4 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

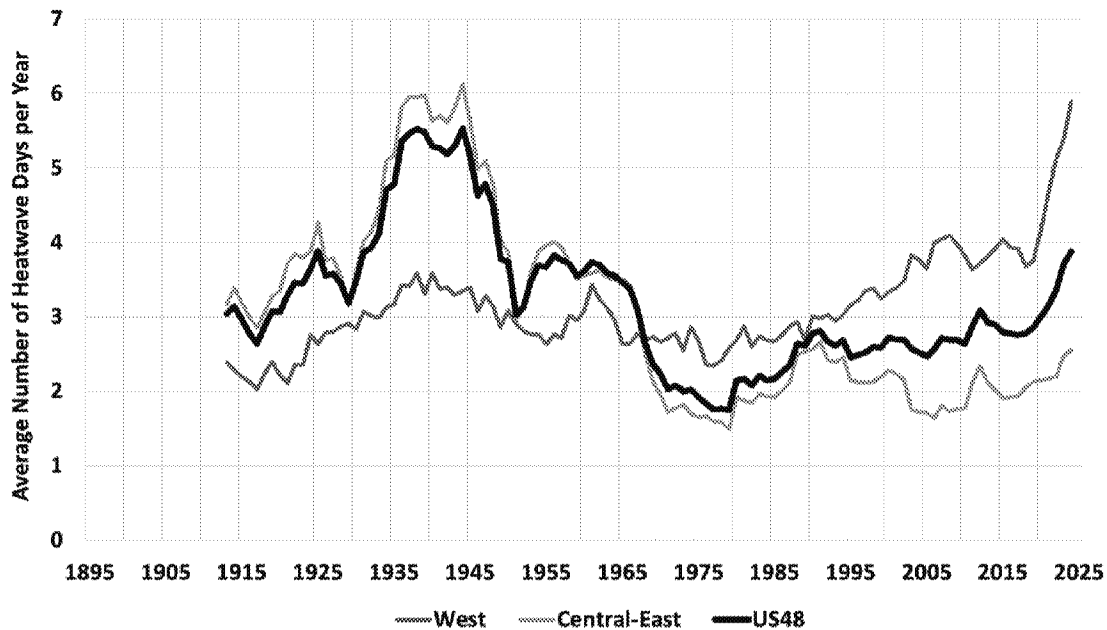


Figure 6.3.6 15-year trailing average of number of heatwave days per year per station in the CONUS (black line) and four regions: West (red), Central-east (green).

Figure 6.3.6 indicates that there are regional variations in heatwave activity. The excessive heat of the first half of the 20th century occurred primarily in the eastern two-thirds of the nation, while the West has seen a recent increase of heatwave days (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago, consistent with the upper panel of our Figure 6.4.1 taken from NCA4.

This metric varies significantly with region. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

The analysis of heatwaves is an example of why it is important to consider complete datasets and appropriate metrics. The NCA5 directs readers to the website [[HYPERLINK](#)

"<https://www.globalchange.gov/indicators/heat-waves>"] (USGCRP 2023) to view a figure showing the number of urban heatwaves by decade from the 1960s, which we reproduce as Figure 6.3.7.

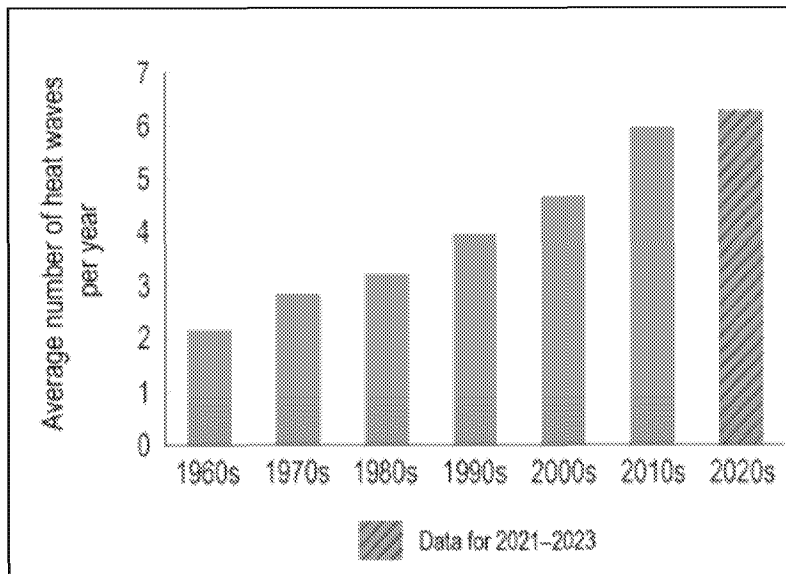


Figure 6.3.7: Average number of urban heatwaves per year for 50 large U.S. metropolitan areas. From [[HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"](https://www.globalchange.gov/indicators/heat-waves)]

The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave used is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the *minimum* apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

Given the unusual heatwave definition and urban focus, these increasing values since 1960 presented in USGCRP (2023) are not informative about long term trends or the influence of GHG emissions for at least two reasons. First, as shown in Figures 6.3.1 and 6.3.6, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. Second, post-1960 urbanization in these cities is a major factor in the rise of T_{min} relative to co-located T_{max} and relative to T_{min} at nearby rural stations. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer T_{max} (especially in rural areas) is a better metric for detecting changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

6.4 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of **heavy precipitation events have increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the **magnitude and intensity of extreme precipitation has *very likely* increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme precipitation events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast using a trend model with a non-parametric variance estimator robust to the complex autocorrelation properties of precipitation data. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

These findings have been updated for this report with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 27 stations in the Northeast (1888ff from Buffalo NY to Eastport ME). The locations are shown in Figure 6.4.2. The stations were selected on the basis of availability of long-term high-quality records. The regions are each associated with important features of extreme precipitation behavior. The Pacific coast is associated with landfalling atmospheric rivers. The NCA report has indicated that the Northeast has experienced the greatest increase in extreme events. The Southeast is also a place noted in the NCAs for increased extreme events.



Figure 6.4.2: Locations of precipitation monitoring stations used in this report. Orange: Pacific coast. Blue: Northeast. Green: Southeast.

The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.

Pacific Coast heavy rainfall events

- Average precipitation trend is statistically significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst series of such events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862; it dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

BOX: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent years. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the

two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ArkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, a 130-year span contains 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation, then the total number of these events across all stations should be evenly spread out over the years. In Fig. 6.5.3 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of such precipitation metrics, there is no indication of a tendency to become more frequent over time.

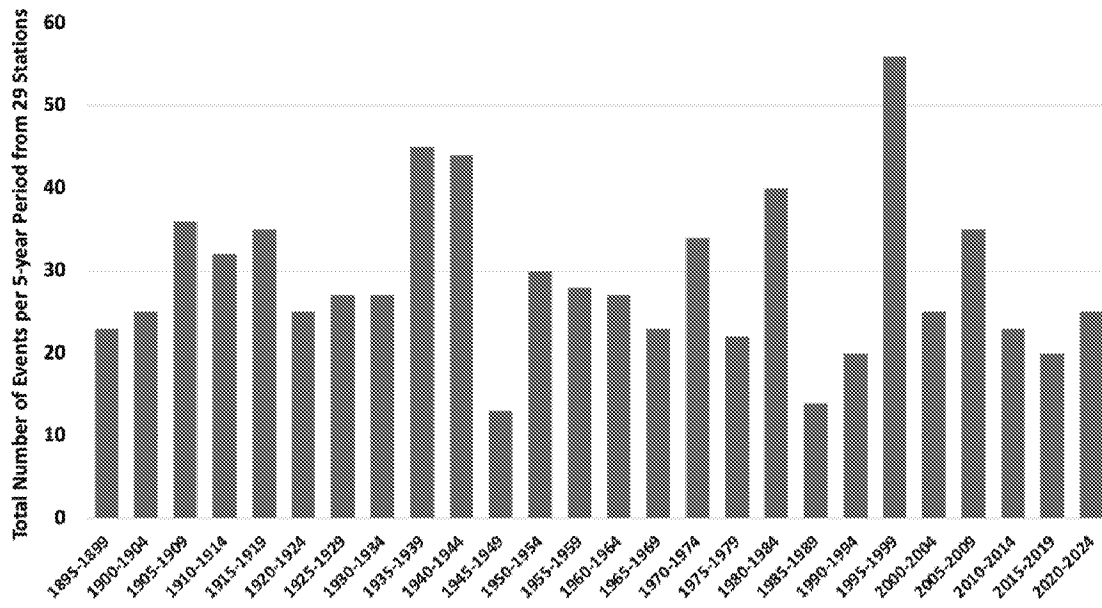


Figure 6.5.3. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

Southeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.5.4 shows the same calculation for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 -- an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

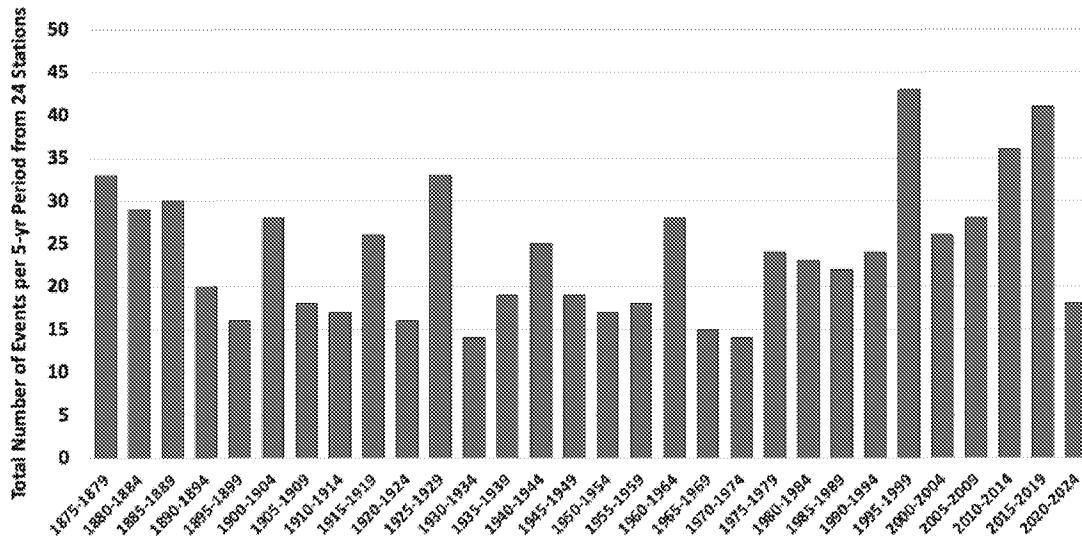


Figure 6.5.4. As in Fig. 6.5.3 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in 12 of 27 locations and also in the regional average.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY, Buffalo NY and Eastport ME, but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME, Gardiner ME and Eastport ME, but insignificant elsewhere.
- When averaged over all stations in the region, there is no statistically significant trend in either the precipitation variance or maximum

Fig. 6.5.5 shows the same calculation for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest temporal variations in time. In this region, 72% of events occur during June to October and are dominated by incursions of hurricanes, tropical storms, or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it merits a closer examination.

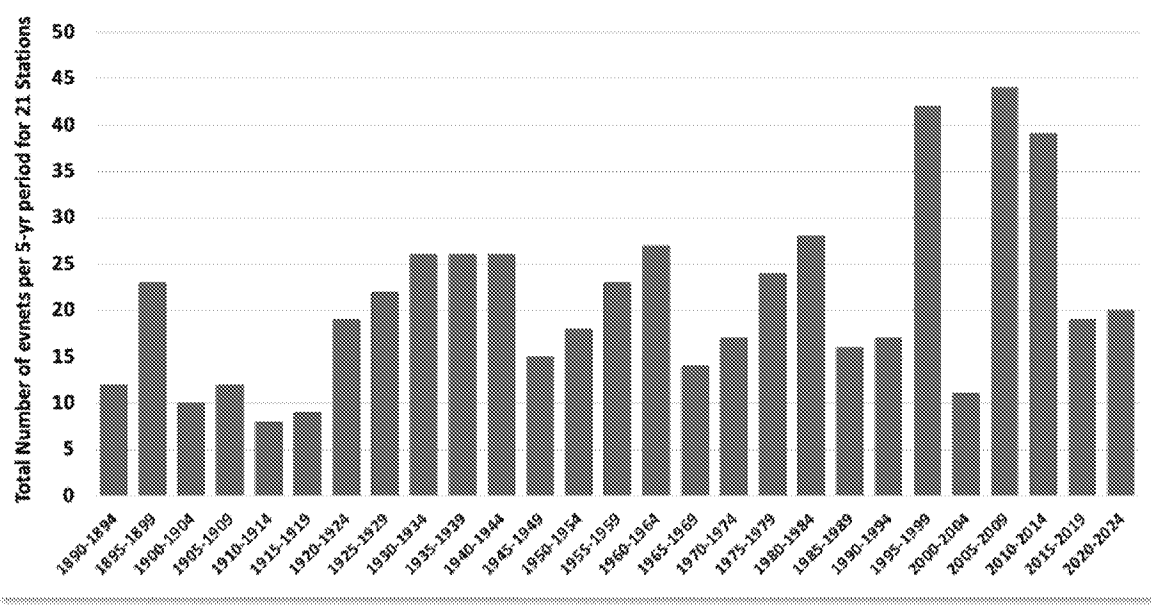


Figure 6.5.5. As in Fig. 6.5.3 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 27 Northeast stations from NY to ME, including Montreal.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth et al. (2019) examined a similar region as in Fig. 6.5.5 that includes PA and NJ and reported significant differences between two 18-year periods, 1979-96 and 1997-2014, of various precipitation extremes, including a 317% increase in 24-hr events exceeding 6 inches, while we find a 51% increase over the same years. However, Figure 6.5.5 shows that frequency drops sharply after 2014, returning to the long-term average in the subsequent 5 year intervals, again illustrating the perils of drawing conclusions from short-term trends in highly variable metrics.

Also the high percentage increase in the Howarth et al. sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.5.6 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only +0.02"/decade. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.5.5 and 6.5.6 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, there was no regional pattern and the change did not persist beyond 2014.

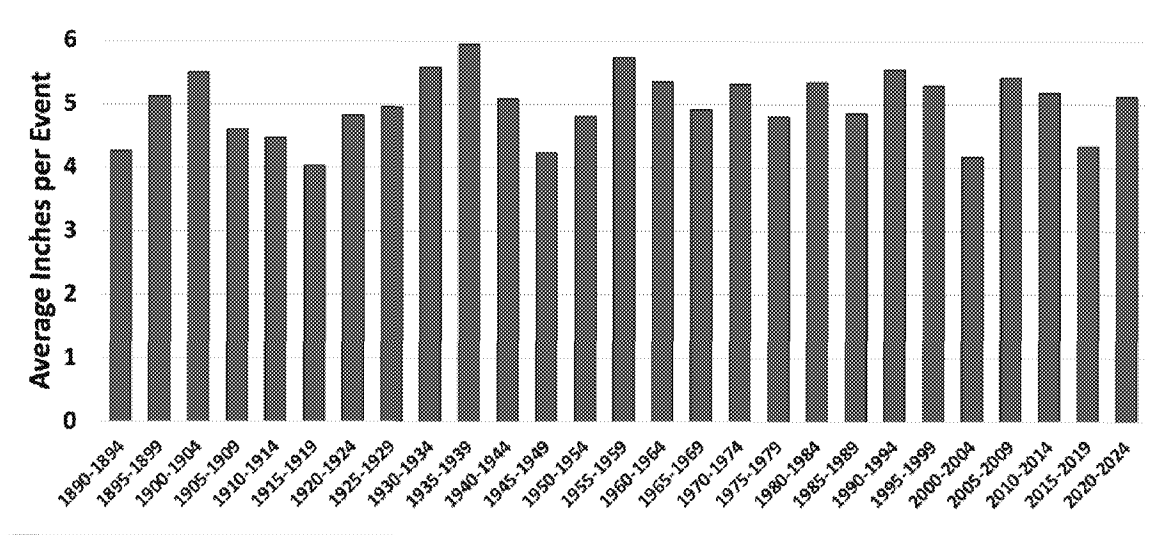


Figure 6.5.6. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.5.6 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.5.5.

In summary, some regions show short-interval increases in extreme precipitation events, consistent with natural variability. But analysis of long term, nationwide historical records taking into account the autocorrelation properties of precipitation data does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.5 Tornadoes

AR6 assesses tornado trends in the US as follows:

[O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

The monitoring of weak tornadoes has changed over time. The growth of rural populations and the increasing ability to take video with hand-held devices has led to more frequent reports of weak tornadoes that produce minimal damage. In contrast, strong to violent tornadoes have been observed more consistently over time. Since statistics began in 1950, there has been a substantial decrease (by about 50%) in the number of strong to violent tornadoes as shown in Fig. 6.6.1a. Note that tornado strength is measured by the damage it produces, not by the visual appearance of the funnel. Limited real-time observational capabilities in earlier decades did not prevent identification because strong to violent tornadoes leave much more damage which will be assessed later even if the tornado itself was not observed.

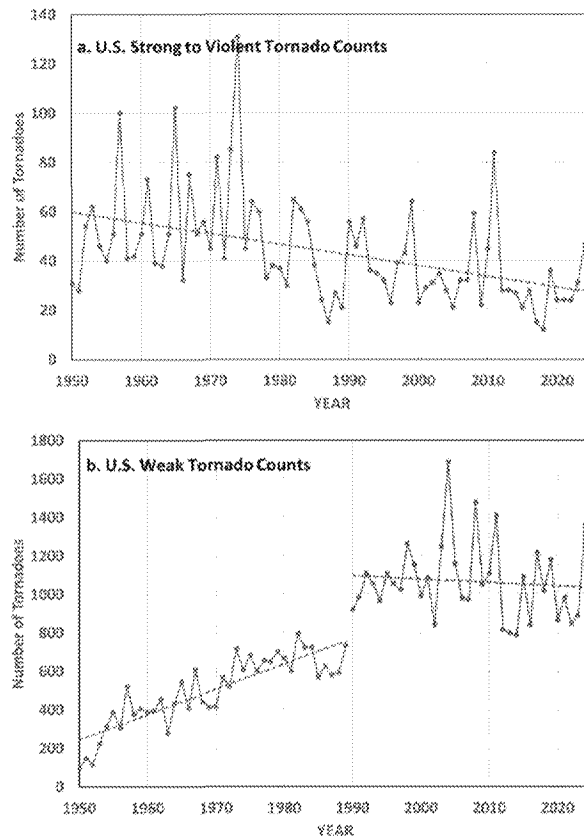


Figure 6.6.1. Annual U.S. tornado counts for (a) strong to violent tornadoes (EF3 to EF5), and (b) weak tornadoes (EF0 to EF2). Based upon NOAA Storms Prediction Center data, available at https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv

To summarize, there is a noticeable downward trend in the number of severe tornadoes in the U.S. since 1950. After 1990 the number of weak tornadoes in the U.S. has remained roughly constant; data before that are incomplete due to limited monitoring.

6.6 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX **assessed *low confidence* for observed changes in the magnitude or frequency of floods** at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is ***low***.” (Chapter 11.5)

NCA4: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude **but does not provide robust evidence** that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in Section 6.5 of absence of coherent changes in extreme precipitation.

6.7 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “**Increasing trends in agricultural and ecological droughts have been observed on all continents** (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA4: “As a consequence of this increased precipitation, **drought statistics over the entire CONUS have declined.**” (p. 233)

NCA4: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, **recent droughts are not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 6.8.1, US long term data shows an insignificantly declining trend toward extreme dryness (-0.000001% per year)

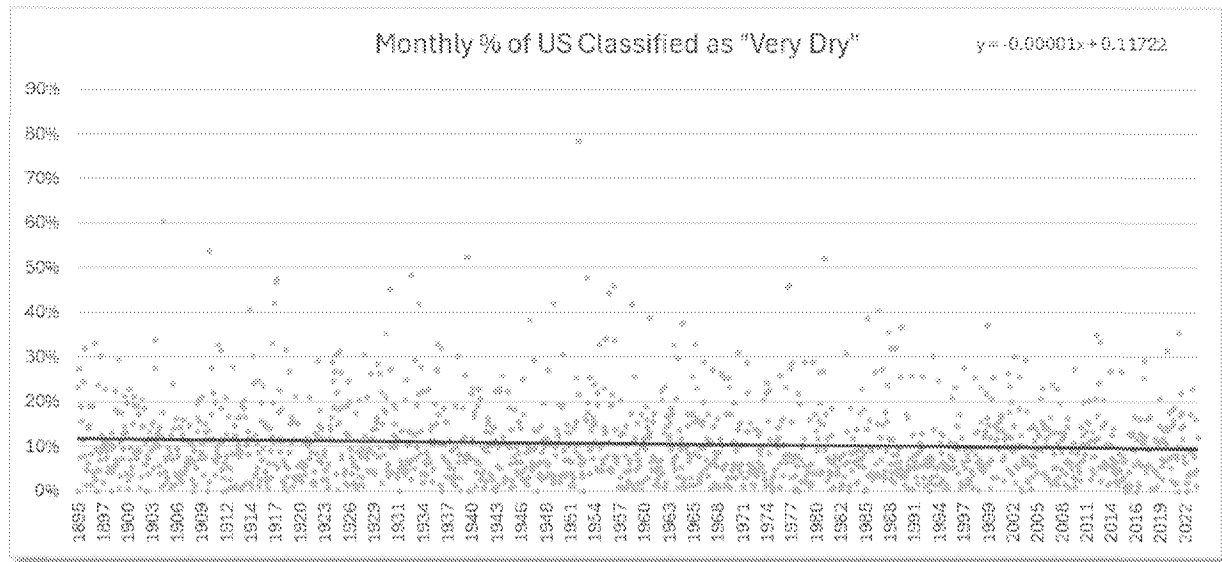


Figure 6.8.1: US dryness (%) 1895—2023. Source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)]

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

In summary there is no evidence of increasing drought frequency or intensity in the U.S. or globally over recent decades.

6.8 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.

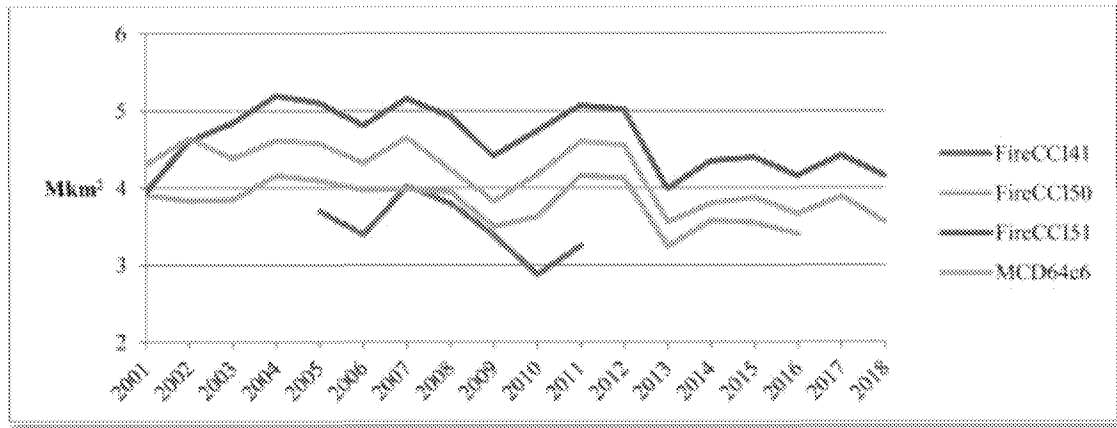


Figure 6.9.1: Global wildfire area 2001-2018. Source: From Lizundia-Loiola et al. (2021). The different coloured lines represent data products derived from different satellites and algorithms

Global data show that wildfire coverage is constant or declining on every continent (Samborska and Ritchie, 2024).

Active fire suppression since 1900 makes it difficult to establish a natural baseline for wildfire activity in the U.S. Paleoclimatic evidence indicates that past activity was much higher than today. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years and also fit a model to predict fire activity as a function of climatic conditions. Their results are summarized in Figure 6.9.3 below (from Figure 2 in their paper). There has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century, it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

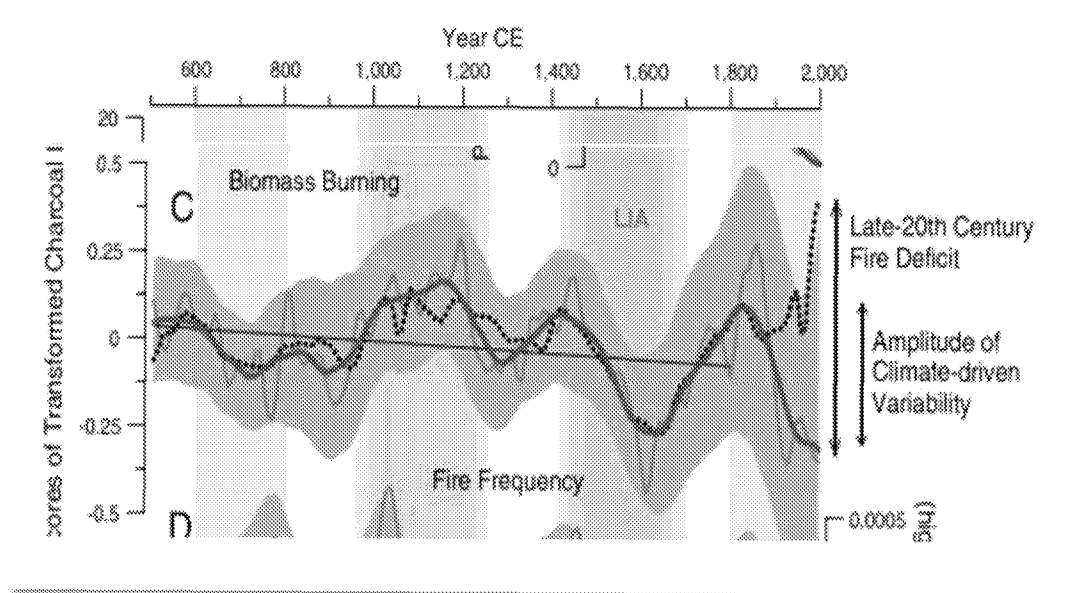


Figure 6.9.2 Fire frequency and fire deficit in the US. The red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based climatic conditions. model. Source: Copied from Marlon et al. (2012)

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.9.2.

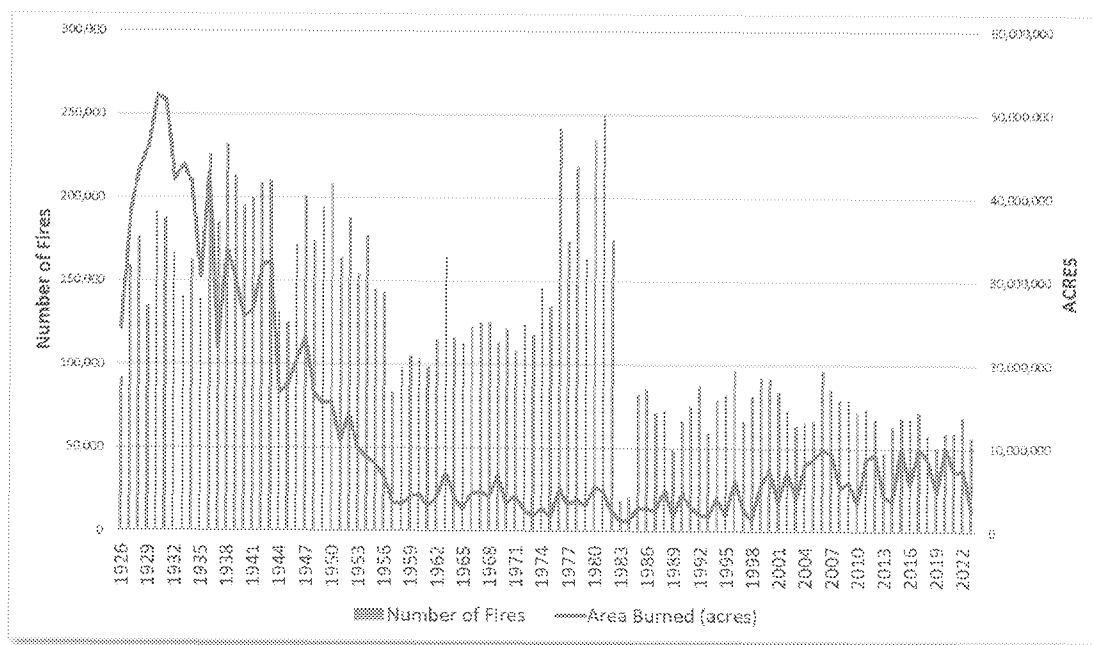


Figure 6.9.2: US wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Center data

Pre-2017 webarchive.org.

The NIFC has removed the pre-1960 data from its current website on the grounds that measurement methods changed after 1960 making the comparison unreliable. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple, 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society, 2022). This led to the 10 am rule in 1935 requiring that all fires spotted on any day had to be controlled by 10 am the following day (National Forest Foundation, 2022).

While defeating all fires seemed a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service, 2022). Over time the U.S. Forest Service has begun to rethink its goals, recognizing that new approaches such as prescribed burns, fuel elimination, and controlled wildfires are more appropriate (Sommer, 2016). Recent research is validating this approach and recognizing that more frequent smaller fires likely result in the healthier forests, water ecosystems and biodiversity (Stephens et al., 2021).

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7 CHANGES IN SEA LEVEL

Chapter Summary

Since 1900, global average sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions - each of these locations is associated with substantial local land sinking (subsidence) unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. US tide gauge measurements shown herein reveal no obvious acceleration beyond the historical average rate of sea level rise.

7.1 Global sea level rise

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of the volume of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (B. Fox-Kemper et al., 2021). The rate of global sea level rise is estimated to be 0.12 inches/year (for reference, 0.12 in is the height of two stacked pennies) (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860, well before most anthropogenic greenhouse gas emissions.

7.2 U.S. sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 7.1 shows that in Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast tide gauges show rises between 0.12 inches/year, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. That latter, which varies from place to place, is

best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (G Wöppelmann and M Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (e.g. for urban development purposes) and subsurface extraction of groundwater, oil, or gas.

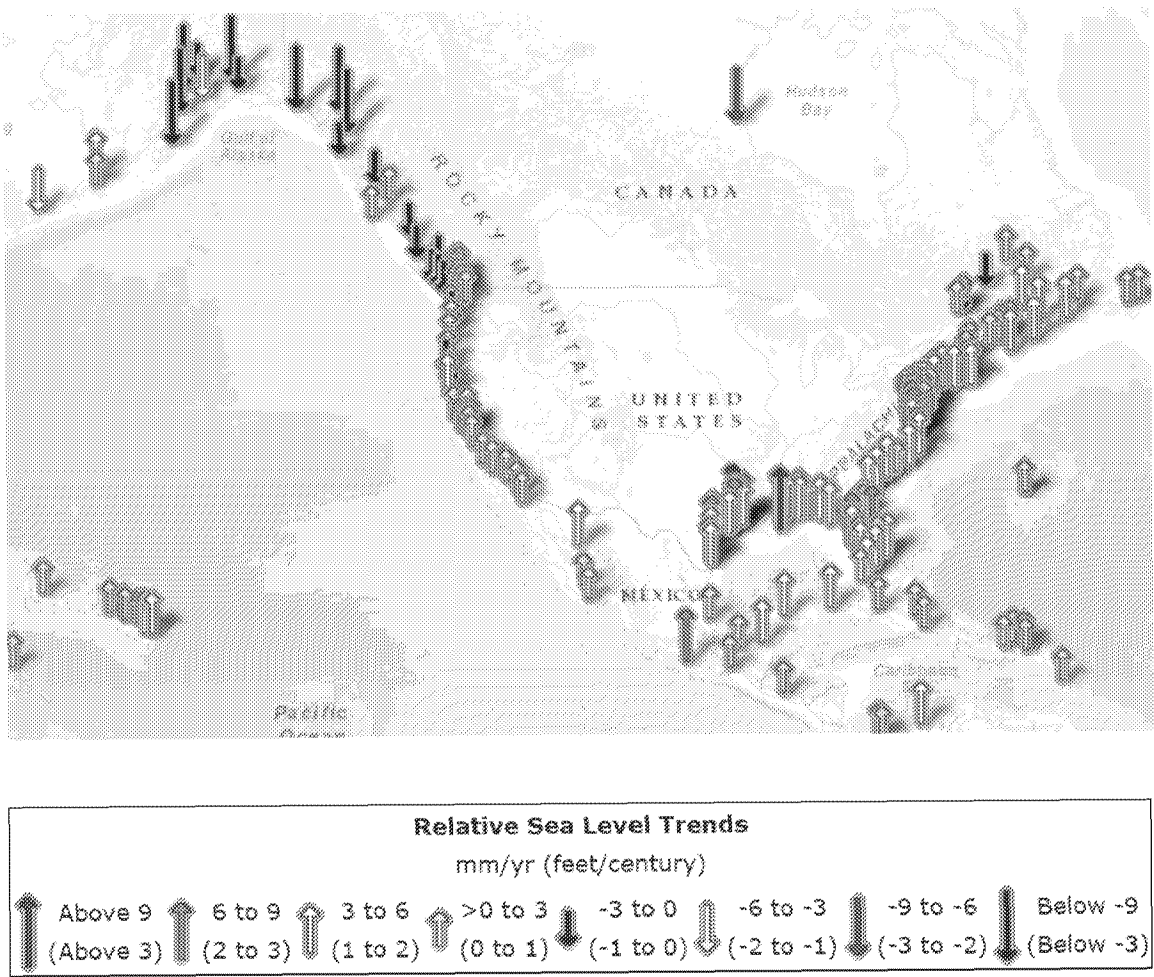


Figure 7.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/sltrends/>). For reference, 3 mm = 0.12 in.

Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; Letetrel et al., 2015; Karegar et al., 2016). The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

Table 7.1 Absolute sea level rise (inches/year) (Relative Sea Level Rise (RSLR) plus Vertical Land Motion (VLM))

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.2). As shown in Table 7.1, San Francisco’s vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (M Shirzaei and R Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, have been caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

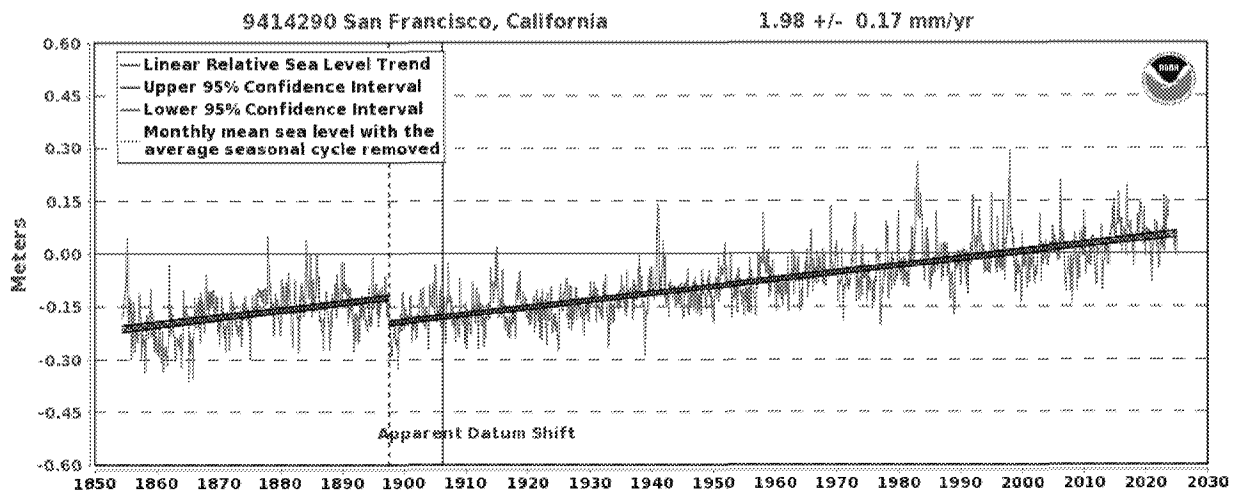


Figure 7.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (Kasmarek and Ramage), which caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes have been the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the deadliest U.S. natural disaster (Weems, 2016). Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula, literally removing significant portions of the land mass (UCS, 2017). While only 17 people were killed in Texas, property damage exceeded \$50 billion (White, 2017). In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages (NOAA, 2025).

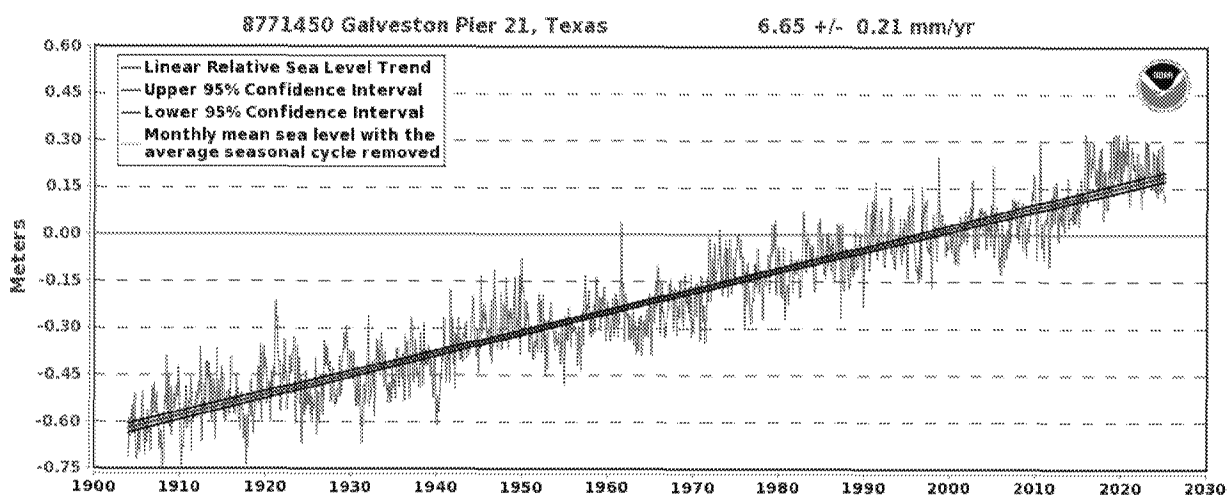


Figure 7.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 7.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 7.1 gives the absolute sea level rise as +0.08 inches/year.

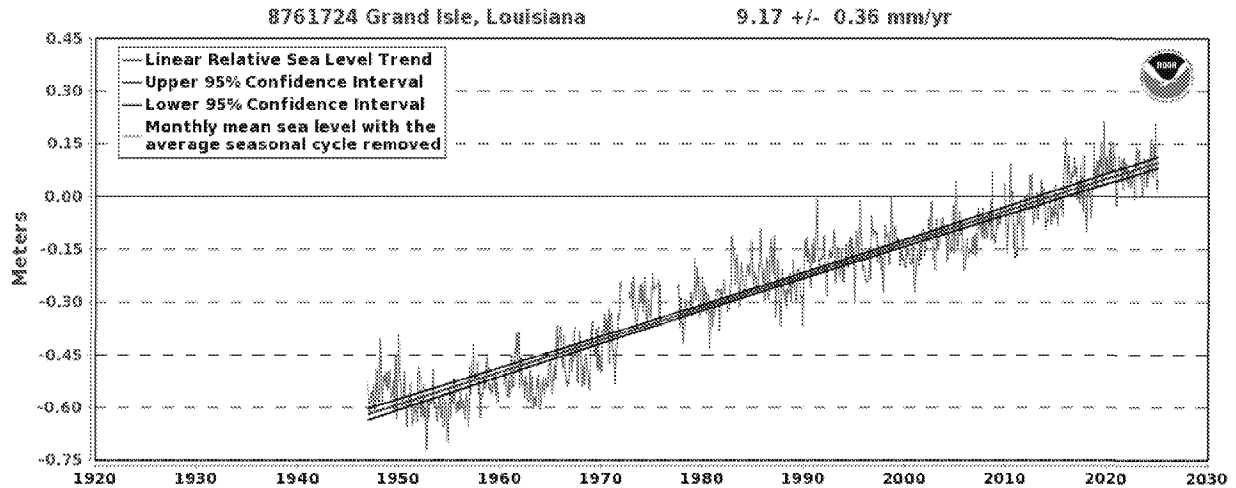


Figure 7.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi's suspended sediment load by ~50% (Malooney, 2018). A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (Neinhuis et al., 2017), associated with groundwater and resource withdrawal. As the city's elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans' problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (The Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 7.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55% of the measured relative sea level rise.

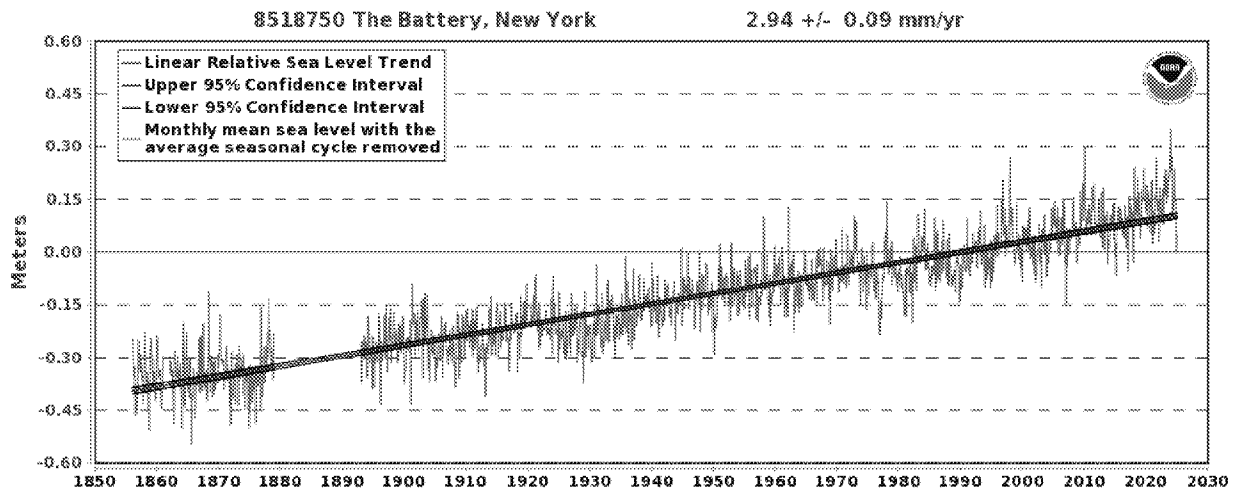


Figure 7.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Superstorm Sandy, New York developed a comprehensive plan: [[HYPERLINK "http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf"](http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf)] (CNY,2013). A broad range of coastal protection measures are outlined that match the risks facing the various zones: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

7.3 Projected sea level rise

The concern over sea level rise is not about the roughly 8 inches of global rise since 1900. Rather, it is about projections of *accelerated* rise based upon simulations of a warming climate through the 21st Century.

The IPCC AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (Fox-Kemper et al., 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (Fox-Kemper et al., 2021). There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 7.2-7.5, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

In February 2022, NOAA issued its projections of sea level rise for various sites along the US coast (Sweet et al, 2022). They claim that by 2050, the sea will have risen one foot at The Battery in Manhattan. A one foot rise in thirty years would be more than twice the current rate and about three times the average rate over the past century. In that historical context, NOAA's projection is remarkable—as shown in Figure 7.6, it would require a dramatic acceleration beyond anything observed in the early 20th century. But even more noteworthy is that they say this rise is “locked in”—it will happen no matter what future emissions are. We should know in a decade or so whether that prediction has legs.

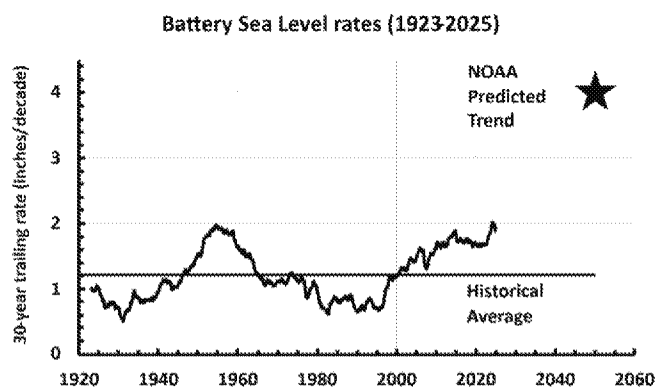


Figure 7.6 Rate of sea level rise at the Battery in Manhattan. Shown is the historical thirty-year trailing trend, together with the allegedly “locked in” NOAA predicted trend for 2050. Historical data: NOAA Tides and Current.

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8 UNCERTAINTIES IN CLIMATE CHANGE ATTRIBUTION

Chapter summary

“Attribution” refers to determining cause regarding some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not in general make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (e.g. event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially those for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. AR4 Working Group I (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

AR5 Working Group II (Cramer et al., 2014) makes the following statement:

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The IPCC employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC.

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals

- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings might have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 6, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 Natural climate variability

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850-1900. As discussed below, this minimal contribution of natural variability has been disputed by several publications that question the magnitudes of solar variability and internal variability from large-scale ocean circulation.

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was very small (0.05 W/m^2 , Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was still assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate - something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

The change of TSI over time remains a challenging problem.. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibits non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used to calibrate proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

This uncertainty causes some reconstructions of TSI from 1750 to have low variability (implying a very low impact of solar variations on global mean surface temperature) whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). The choice of TSI satellite record used in an analysis can therefore substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, either amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. There are numerous candidate processes, including solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Such solar indirect effects are not included in climate models, although indirect methods of estimating their impacts suggest they are significant. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Nino-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models show have too little amplitude compared to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov et al. 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

“Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (*high confidence*).” (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The time series of global surface temperature anomalies since 1850 (Figure 8.1) shows irregular variations of significant amplitude against the background of an overall warming trend and, after 1976, a pronounced difference in trends between the Northern Hemisphere and the Southern Hemisphere. The period between 1905-1945 shows a strong trend of warming. The following thirty years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

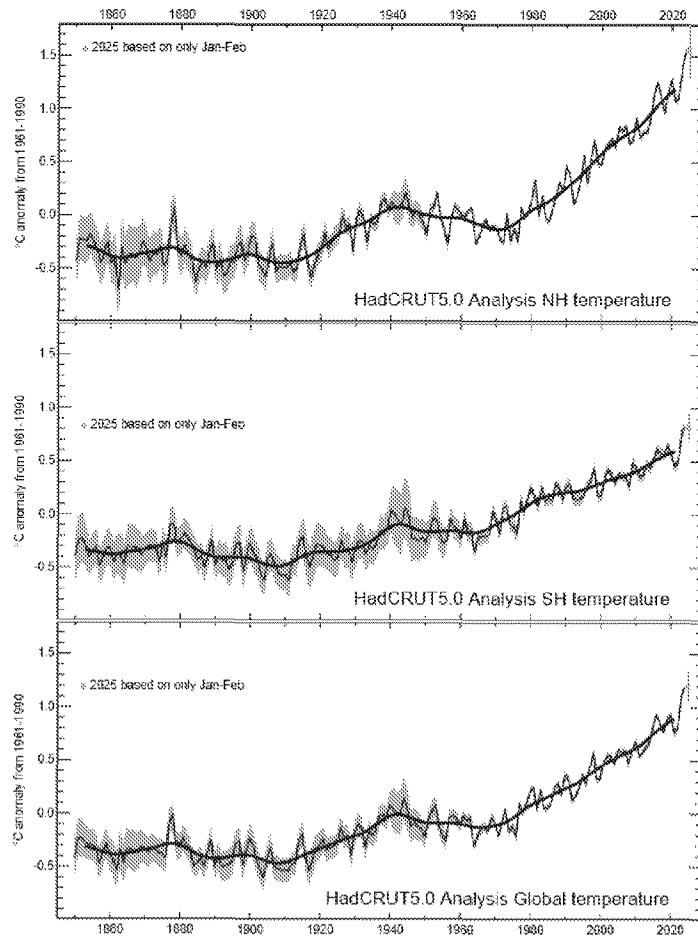


Figure 8.1 Global average surface temperature anomalies 1850—2025. Top: Northern hemisphere. Middle: Southern hemisphere. Bottom: Global average. Source: UK Hadley Centre [[HYPERLINK "https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf"](https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf)]

The causes of the early 20th century warming are discussed by Hegerl et al. (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941; hence this implies that CO₂ had little impact on the warming. Volcanic activity during this period was very low, and solar forcing is uncertain. Hegerl et al (2017) somehow inferred that 40-54% of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman et al (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular Mode was positive, with a strengthened Amundsen–Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid century was particularly pronounced in the Arctic. Bokuchava and Semenov (2021) find that most likely these variations were caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural radiative forcing related to the reduced volcanic activity and variations of solar activity as well as growing greenhouse gases concentrations. Tokinaga et al (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic

warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale circulations over the Northern Hemisphere; these same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation; cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson et al. (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Nino and La Nina events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

8.3.2 *Optimal fingerprinting*

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or “fingerprints”) associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of “signals”, which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the research literature. While it has been widely used and prominently featured by the IPCC since 2001 there is very little literature examining the statistical properties of the results it generates. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

A series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that practices adopted from econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone

among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions that easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that used TLS for optimal fingerprinting without verifying its applicability in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics that are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which is consistent with the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not falsify all results stemming from the IPCC optimal fingerprinting method, they do challenge the basis on which they were believed to be correct.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. These have the advantage of not depending on assumptions about the accuracy of climate models, but the disadvantage that they depend on difficult-to-test assumptions about the data generating process underlying climate and forcing data. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al., 2016, Balcombe et al., 2019, Dagsvik et al., 2020, Razzak, 2022, Dagsvik and Moen, 2023).

“Granger causality” modeling is a tool for determining directions of influence in data series that move together. It is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error in Al Gore’s documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback of CO₂ levels on temperature.

In summary, the primary statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently

been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Declining planetary albedo and recent record warmth

A sharp recent increase in global average temperatures has raised the question of short-term drivers of climate. One such candidate is the fraction of absorbed solar radiation which has also changed abruptly in recent years. The question to be answered is whether the change is an internal feedback to warming caused by greenhouse gases or whether something else changed the fraction of absorbed radiation which then caused the recent warming.

The albedo is the fraction of incoming solar radiation that is reflected back into space rather than being absorbed by the planet. Highly reflective surfaces like cloud tops and snow and ice are most important in this regard. The Earth's albedo is approximately 30%, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed by the planet to be then re-radiated as heat. Hence, other things being equal, a decline in albedo is associated with a warming of the Earth.

Arguably the most striking change in the Earth's climate system during the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure 8.1 shows the planetary albedo variations since 2000, when there are good satellite observations. The 0.5% reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in solar energy averaged over the planet (Hansen and Karecha, 2025). For comparison, the IPCC estimate of forcing from the increase in atmospheric CO₂ compared to preindustrial times is approximately 2.2 W/m² (Figure 3.1.2).

Looking back prior to 2000 with less adequate data, Gossling et al. (2025) assessed that planetary albedo was relatively low around the 1940's and 50's, before rising industrial aerosol precursor emissions increased albedo until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum may have been the lowest since at least 1940.

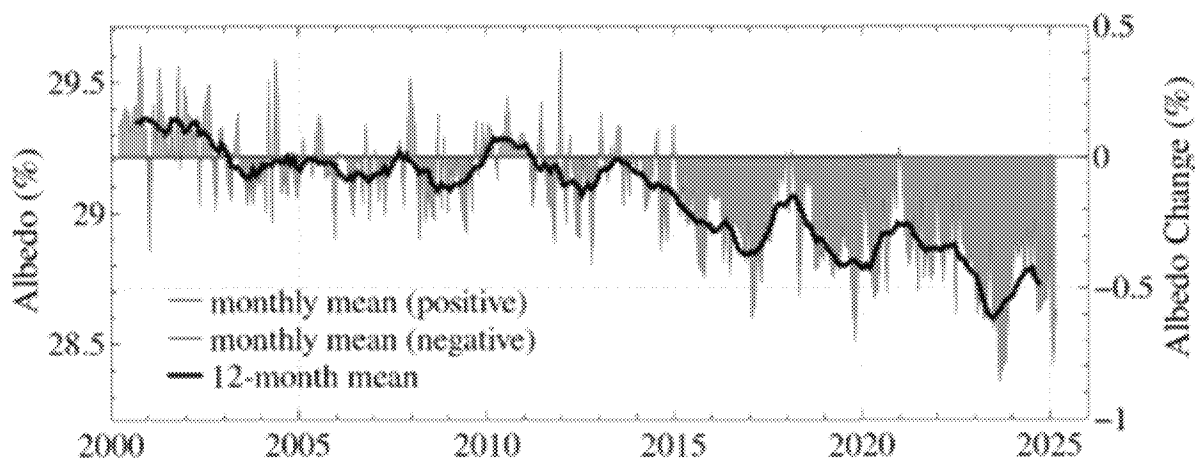


Figure 8.1. Earth’s albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface characteristics can’t explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5% since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England et al., 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that “There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability.” (SPM, A.1.5)
- Northern hemispheric annual snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer.
[HYPERLINK "<http://climate.rutgers.edu/snowcover/>"]
- Global greening (Chapter 2) is contributing to the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo increase associated with increasing forested area.

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. For anthropogenic aerosols, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth’s radiation balance (Hodnebrog et al., 2024; Yuan et al., 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the Northern hemisphere, whereas in the Southern hemisphere the decrease in planetary albedo is primarily due to decreases in mid-level clouds across all latitude zones. Gossling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

The question then becomes what caused the change in cloud cover. Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Nino event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al. 2021).
- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Nino Southern Oscillation (ENSO) have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gossling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz et al, 2025; Kuchar et al., 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

8.5 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest in assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first column of Table 12.12 in Ranasinghe et al. (2021, p. 1856), reproduced here as Table 8.1, summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	4
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fire weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	11
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwave	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease	Medium confidence of decrease	Low confidence in direction of change	Medium confidence of increase	High confidence of increase
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Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

Out of the 33 weather impact categories an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence* assertions, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Columns 2 and 3 of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We have omitted these columns for several reasons. First, because they refer to whether climate models project detectable signals in the observations, which is a very different question than our concern here, whether a signal has been detected in historical data. Second, as we discuss in Chapter 4, the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Third, the ensemble of detailed models is acknowledged (Palmer and Stevens 2019) to be “not fit for purpose” in describing regional changes and “unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided.” (Nissan et al, 2019)). Even with these caveats, we note that the omitted columns in AR6 Table 12.12 indicate most weather impacts are not expected to exhibit an anthropogenic signal this century.

As we discussed in Chapter 7 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

Citations Palmer [[HYPERLINK "https://www.pnas.org/doi/full/10.1073/pnas.1906691116"](https://www.pnas.org/doi/full/10.1073/pnas.1906691116)]

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8.6 Extreme event attribution (EEA)

Examining the IPCC’s treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted above, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of particular extreme weather events. The most prominent effort is World Weather Attribution (WWA; worldweatherattribution.org), an international research initiative for extreme event attribution that purports to analyze how climate change influences the likelihood and intensity of extreme weather events. Their approach is to use large ensembles of regional climate models to compare the event in today's climate with a counterfactual pre-industrial climate without human influences.

WWA has a prominent public presence in linking extreme weather to climate change, with its press releases attracting considerable attention in public and policy discussions. However, the WWA's extensive promotion of non-peer-reviewed findings, its funding ties, its open admission to shaping analyses to serve litigation, and its methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of their conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to influence climate science and media narratives. Technical criticisms of the approach include a lack of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by greenhouse gases; and a failure to adequately account for internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean that a climate change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore, the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al., 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

We provide a case study of a recent high impact extreme event in the U.S. to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.6.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme event that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team generated international headlines with their analysis, which provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important counter to the first claim is that other researchers concluded from historical weather data that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman, 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman, 2023, p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking mid-tropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking mid-tropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using

a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

Bercos-Hickey et al. (2022) conducted a statistical analysis of a model-based attribution study of this heat wave. Because the event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave - they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022, the WWA analysis) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analyses showed that the event was caused by rare meteorological conditions that were not made more probable by global warming.

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PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY

9 CLIMATE CHANGE AND US AGRICULTURE

Chapter summary

There is abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behavior by farmers, has been beneficial for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from or be harmed by climate change, once the adaptive responses of farmers are considered the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn et al. (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn et al. method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached conclusions similar to Mendelsohn et al. (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the US agricultural sector. However, a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in US agriculture due to climate warming.

Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and

20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2 CO₂ is a major driver of plant growth, so this omission biases the analysis towards underestimation of the benefits of climate change to agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiment” or FACE plots, in which small sources of CO₂ are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth et al. (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm caused an average 18% increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key US agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations improved photosynthesis rate, water use efficiency, and growth (Li, 2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. There were also ten studies reporting on +600 ppm CO₂ enrichment, which increased photosynthesis by an average of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured both the yield and nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported

a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection, growers could select wheat types that best take advantage of the elevated CO₂.

Further evidence

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted U.S. crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

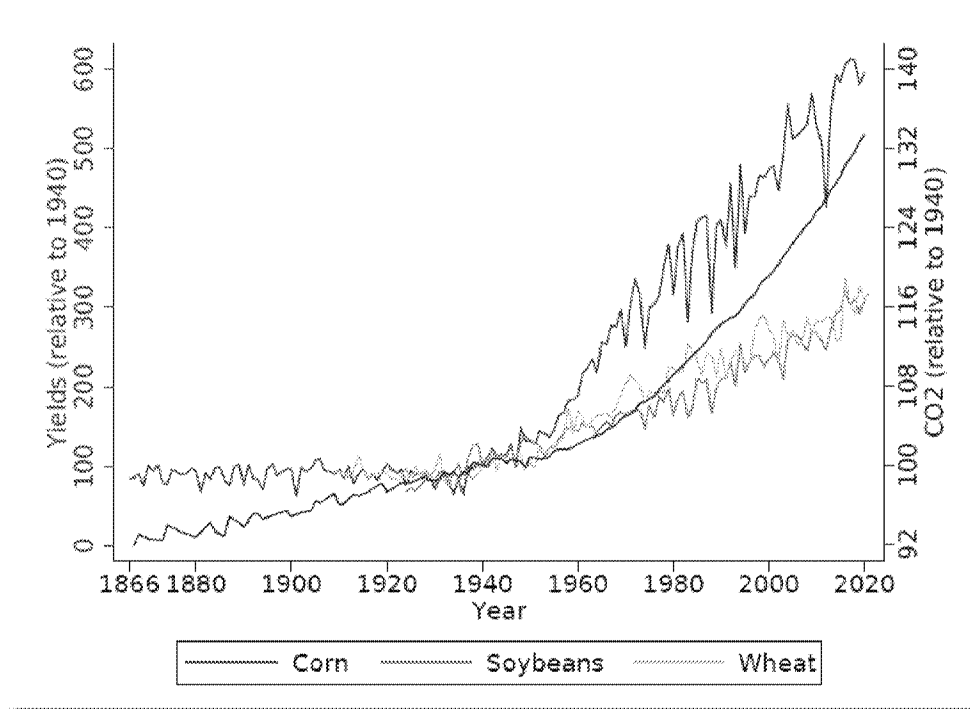


Figure 9.1: US average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100.
Source: Taylor and Schlenker (2021)

Beyond growth benefits, extra CO₂ boosts plant resilience to dryness. Derying et al. (2016) surveyed evidence on crop water productivity (CWP, the yield per unit of water used), drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them; once fertilization was taken into account,

all regions showed a net CWP gain. Deryng et al also reported that negative yield impacts on wheat and soybean were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, observations show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore et al., 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore et al. (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore et al. projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the Moore et al. database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables. He thereby increased the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 10.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

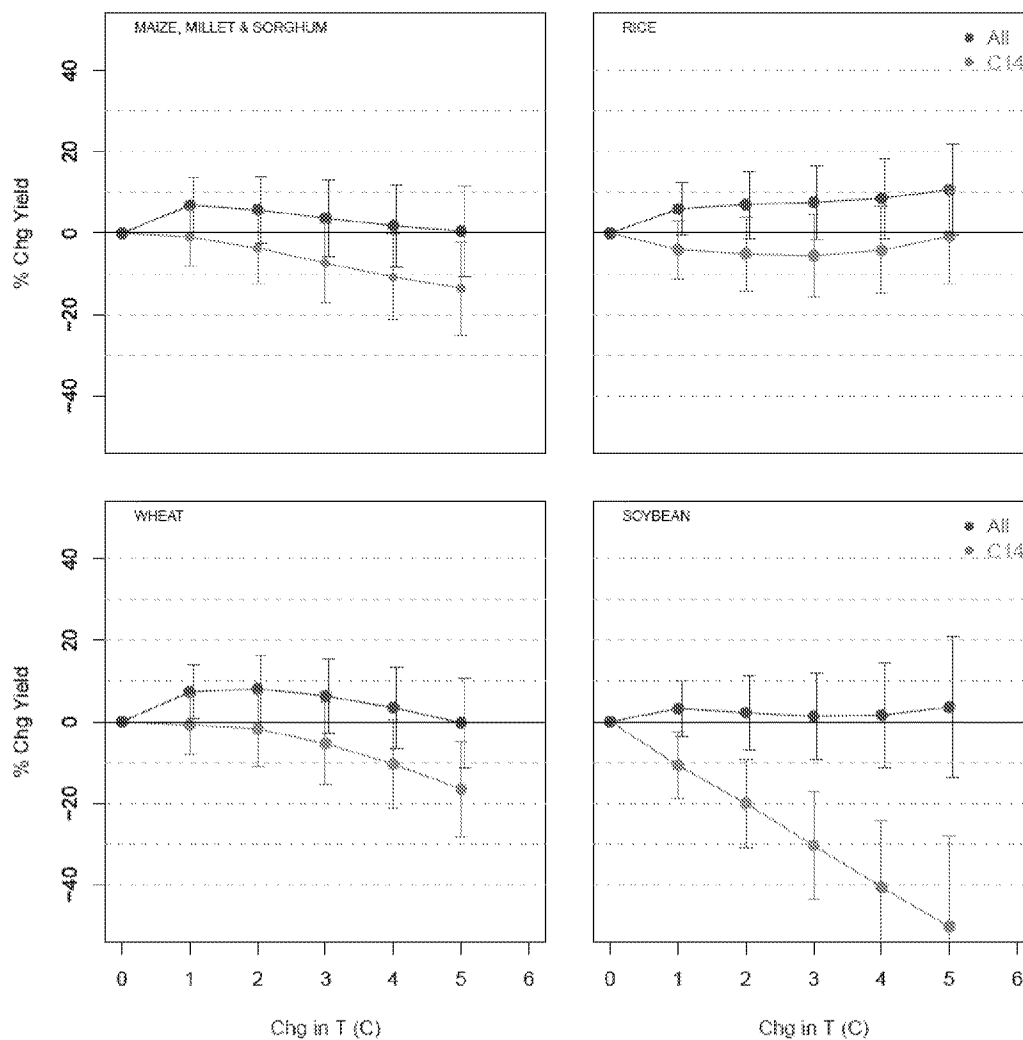


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore et al. (2017). Green: after including omitted data. Source: McKittrick (2025).

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture.

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10 MANAGING RISKS OF EXTREME WEATHER

Chapter summary

Trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase as long as people are able to undertake adaptive responses.

10.1 Socioeconomic context

Risks from human-caused climate change are affected by natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020 (Goklany, 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population) (NOAA, 2025; USCB, 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang, 2023). US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC, 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (NBER, 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA, 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (BMI, 2013). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages (APPA, 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and

other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster as a proportion of GDP have decreased by about 80% since 1980, as shown in the figure below. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments, NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from publication (Pielke Jr., 2025).

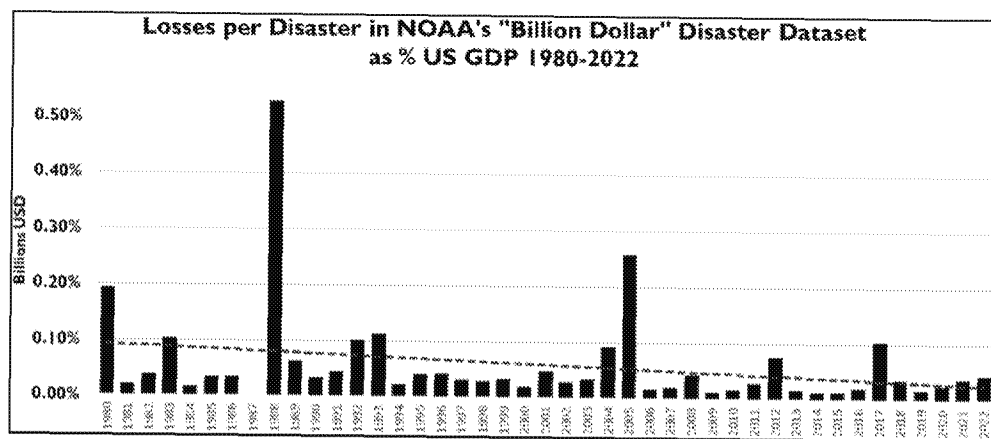


Figure 10.1: Losses per disaster in NOAA’s billion dollar disaster dataset (the version downloaded in July 2023), 1980 to 2022. Source: (Pielke, Jr. 2024)

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. And finally, the US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period though not in the continental US (Chapter 6) and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao et al 2021, Ritchie 20214). Unlike with heat-related mortality. Cold-weather risks set in even at moderately cold conditions (Gasparini et al. 2015, Lee and Dessler 2023). A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7% of deaths were attributable to sub-optimal temperatures, of which 7.4% were attributable to cold and only 0.4% were attributable to heat (Gasparini et al. 2015). In other words cold weather killed 18.5 times as many people as did hot weather.

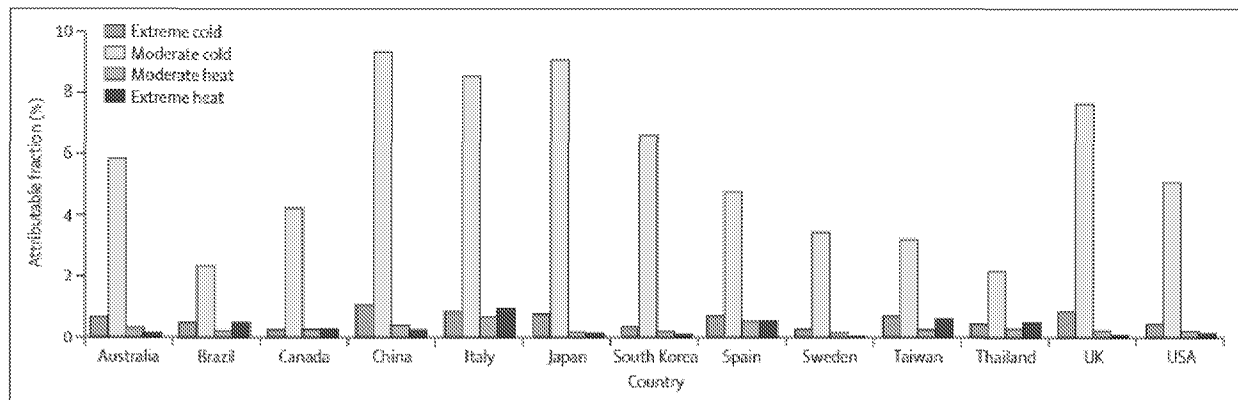


Figure 10.3.1. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini et al. (2015).

Figure 10.3.1 shows the distribution of results from Gasparini et al. (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9%, of which 5.5% was due to cold, thus cold weather killed 14 times as many people as hot weather.

The US EPA reports that, after adjusting for seasonality, the cold-related death rate in the U.S. ([[HYPERLINK "https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths"](https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths) \t "_blank"]) is about twice as large as the heat-related rate (see [[HYPERLINK "https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths"](https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths)] and ([[HYPERLINK "https://www.epa.gov/climate-indicators/climate-change-indicators-heat-related-deaths"](https://www.epa.gov/climate-indicators/climate-change-indicators-heat-related-deaths) \t "_blank"])).

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86% of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60% decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million

deaths in 211 U.S. cities from 1962 to 2006. Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill et al. 2022) acknowledges that heat-related mortality risk is declining over time:

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that

“Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

10.3.2 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels ($< 5^{\circ}\text{C}$) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days ($>30^{\circ}\text{C}$) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

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11 CLIMATE CHANGE, THE ECONOMY AND THE SOCIAL COST OF CARBON

Chapter summary

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the AR5. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC (i.e. a social benefit of emissions). The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points at present does not justify major revisions to SCC estimates.

11.1 Climate change and economic growth

11.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus, 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society always adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects of climate change on US economic activity would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

That statement is validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty!

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen, 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr, 2018, 2020) as have mortality risks (Formetta and Feyen, 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick, 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al., 2021). The following chart is illustrative:

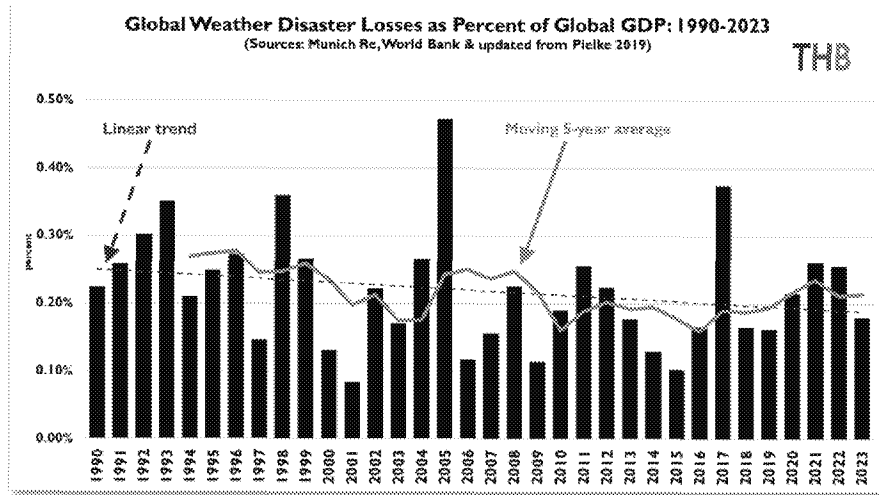


Figure 11.1 Global weather losses as a fraction of GDP. Source: Pielke Jr. (2023)

For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future, 2025). Nordhaus’ work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus, 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus’ Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models.

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we modestly scale back fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

11.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell et al. (2012, herein DJO12) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJO12 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJO12-type results on the same subset of countries as used in DJO12 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang et al. (2023) updated the DJO12 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans –86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJO12 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is taken into account the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9% compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus’ earlier analysis is that trying to prevent the warming would lead to far less than 398% growth.

To summarize, economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. Figure 11.2, from a 2023 OMB-CEA report, shows the expected decrement in U.S. GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe is indeed negligible.

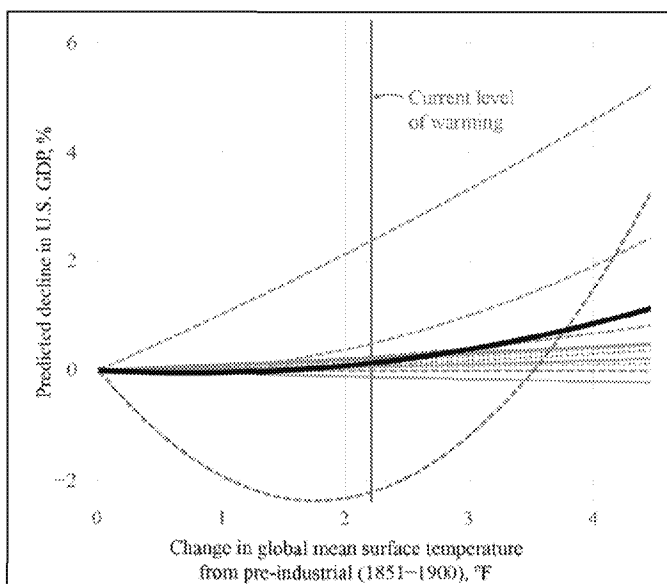


Figure 11.2: Decline in US GDP per degree of warming. Source: XX

11.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

11.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

11.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.

- **Equilibrium Climate Sensitivity:** IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter 9). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- **Damage function coefficients:** IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- **Emission scenarios:** IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- **Abatement costs:** IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But as discussed in Chapter 10, McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA’s SCC revision attributable to agricultural yield losses was unwarranted.

11.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 10 looked at climate change and US agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. In particular Haverd et

al. (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna et al. (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle, 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

11.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon (SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz et al., 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford, 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen et al. 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford, 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the latter is a possibility. Kypke et al. (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of

bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon, 2023).

The possible existence of bifurcations in the Earth's climate system implies abrupt transitions are possible, not just in response to large forcing but to small perturbations as well. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos et al., 2024) and indeed may not be able to since one implication of the "butterfly effect" is the existence of predictability boundaries of nonlinear systems (Palmer et al., 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict or prevent it from happening.

The IPCC AR6 (Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the "tipping point" concept in discussions of climate change (see [[HYPERLINK "https://report-2023.global-tipping-points.org/what-is-a-tipping-point/"](https://report-2023.global-tipping-points.org/what-is-a-tipping-point/)] for example). As summarized by the IPCC AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton et al., 2023). It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate "tipping point" is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of the Greenland and West Antarctic ice sheets. These impacts can be reversed on the decadal timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). The IPCC AR6 WG1 Summary for Policy Makers states:

"The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is high confidence in the 21st century decline, there is only low confidence in the magnitude of the trend. There is medium confidence that there will not be an abrupt collapse before 2100." (C.3.4)

"There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping

points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5)." (B.5.2)

For the purpose of SCC calculations the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. The IPCC AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz et al. incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there may be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been taken into account the result is only a modest increase in the SCC value in the 21st century.

11.2.5 Are there alternatives?

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung, 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the uncertainty of SCC estimates doesn't mean that other regulatory measures are inherently better or more efficient. Many emissions regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) cost far more per tonne of abatement than any mainstream SCC estimate which is sufficient for establishing they fail a cost-benefit test.

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12 GLOBAL CLIMATE IMPACTS OF U.S. EMISSIONS POLICIES

Chapter Summary

U.S. policy actions are expected to have undetectably small direct impacts on the global climate and any effects will emerge only with long delays.

12.1 The scale problem

The emissions rates and atmospheric concentrations of criteria air contaminants are closely connected because their lifetimes are short and their concentrations are small; when local emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since emissions mix globally and the global carbon cycle is vast and slow. Any change in local CO₂ emissions today will have only a very small global effect, and only with a long delay.

Following the emission of a pulse (release) of CO₂ into the atmosphere only about 40 ± 15 percent of the emitted CO₂ will have been sequestered after twenty years. That fraction rises to 75 ± 10 percent after a thousand years, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais et al., 2013, pp. 472-473). Consequently, any reduction in U.S. emissions would only modestly slow, but not prevent, the rise of global CO₂ concentration. And even if global emissions were to stop tomorrow, it take decades or centuries to see a meaningful reduction in the global CO₂ concentration and hence human influences on the climate.

Reducing the atmospheric stock of CO₂ would require emissions to fall below the natural sequestration rate, assuming the entire increase is anthropogenic. Since that rate has been averaging about 50% of emissions in recent decades, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy was too difficult for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected year 2100 level in 2105 instead (Wigley, 1998). Lomborg (2016) estimated that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions will have negligible local effects, and only with a long delay. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” therefore reflects a profound misunderstanding of the scale of the issue.

12.2 Case study: US motor vehicle emissions

The scale problem can be illustrated with reference to U.S. motor vehicles. The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. The 2009 Endangerment Finding therefore

obligated the EPA to regulate emissions from new motor vehicles, ostensibly to reduce or eliminate climate-related harms to the US public.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing US vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to the reduction in global emissions, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0% of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating all US vehicle-based emissions would change the multidecadal warming trend by at most 3%. For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends are determined to a precision of about $\pm 15\%$, so the impact of reducing the rate of global warming by eliminating U.S. vehicle CO₂ emissions would be far below the limits of measurability.

Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

Consequently, in contrast to the case of local air contaminants like particulates and ozone, even the most aggressive regulatory actions on GHG emissions from U.S. vehicles cannot be expected to remediate alleged climate dangers to the US public on any even remotely-measurable scale.

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GLOSSARY

2XCO₂: Doubling of the atmospheric carbon dioxide (CO₂), a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50% of the way to 2XCO₂ compared to 1800.

ABATEMENT: In the context of environmental policy, the reduction of emissions.

ACE (Accumulated Cyclone Energy): A statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds.

ACIDIFICATION: A commonly used term for the reduction in ocean pH from more alkaline to less alkaline values.

ACRIM (Active Cavity Radiometer Irradiance Monitor) GAP: the gap in total solar irradiance data between 1989 and 1991 caused by a delay in the launch of a satellite-borne monitor in time to overlap and intercalibrate with the prior system.

AEROSOLS: Tiny solid or liquid particles suspended in the air.

ALKALINE: Having a chemical pH greater than 7.0. The “opposite” of acidic, which means a pH less than 7.0.

AMBIENT: Relating to the immediate surroundings of something.

ANTHROPOGENIC: Created by humans.

AR (Assessment Reports): Periodic assessments published by the Intergovernmental Panel on Climate Change evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science and the others concerned with societal impacts and mitigation strategies. The most recent was the AR6.

ATTRIBUTION: Assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: The phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: The total quantity or weight of organic matter in a given area or volume.

CARBON: The 6th element in the periodic table. Popularly used as a shorthand term for carbon dioxide.

CMIP (Coupled Model Intercomparison Project): The Intergovernmental Panel on Climate Change's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CONUS: The contiguous 48 U.S. states.

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model developed by William Nordhaus in 1993.

DISCOUNT RATE: The interest rate used to convert future costs and benefits into their present value. Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits.

DRY ICE: Frozen carbon dioxide.

ECONOMETRICS: The branch of economics concerned with the use of statistical methods (chiefly multiple regression) to analyse economic systems.

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: The warm phase of the El Niño – Southern Oscillation, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): The 2009 finding by the Administrator of the Environmental Protection Agency that emissions of well-mixed greenhouse gases (primarily CO₂) endanger human health and welfare.

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean.

FACE: (Free-Air CO₂ Enrichment) Large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: A natural hydrocarbon fuel such as coal, oil, or natural gas formed in the geological past from the remains of living organisms.

FUND (Framework for Uncertainty, Negotiation, and Distribution): An Integrated Assessment Model developed by Richard Tol in 1997.

GBR (Great Barrier Reef): The world's largest coral reef ecosystem located off the northeast coast of Australia.

GDP (Gross Domestic Product): Total market value of all the final goods and services produced within a country's border, usually over one year.

GHCN (Global Historical Climatology Network): A time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: The satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s.

GNP (Gross National Product): Total market value of all the final goods and services produced by the citizens of a country, including exports and imports, usually over one year.

GDP (Gross National Product): Total market value of all the domestically-produced final goods and services produced by the citizens of a country, usually over one year.

GREENHOUSE EFFECT (GHE): The tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): An atmospheric gas that absorbs and emits infrared radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: See long term persistence.

HYDROLOGY: The study of the movement of water, especially on land and in the atmosphere.

IAM (Integrated Assessment Model): A computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions.

IEA (International Energy Agency): A Paris-based intergovernmental organization, established in 1974, that provides policy recommendations, analysis and data on the global energy sector.

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies.

IR (Infrared): Heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: The cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): A form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales.

MAIZE: Corn.

MODEL: A computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes.

MORTALITY: Death or number of deaths, usually expressed for a specific population and period.

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States. There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023).

OECD (Organization for Economic Cooperation and Development): A group of 38 member countries that have a democratic system of government and free economic systems.

PALEOCLIMATE: Climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): A statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds.

PHOTOSYNTHESIS: The process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function).

PPM: Parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: The near-term historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s.

RADIATIVE FEEDBACK: A change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature.

RADIATIVE FORCING: The change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP (Representative Concentration Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC’s Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they

assume in 2100 relative to pre-Industrial times, in Watts per square meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: A method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SCC (Social Cost of Carbon): An estimate of the net economic damages, measured in present-value dollars, caused by emitting one additional ton of CO₂ into the atmosphere.

SSP (Shared Socioeconomic Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: Tropical cyclone.

TMAX: The daily maximum surface air temperature.

TMIN: The daily minimum surface air temperature.

TOA: Top of atmosphere.

TOXICOLOGY: The study of the adverse effects of chemical substances on living organisms.

TREND: A coefficient, usually estimated using linear regression, representing the slope of a line of best fit through a time series of data, indicating any tendency for the series mean to move up or down over time.

TSI (Total Solar Irradiance): The measure of the total amount of incident solar radiation per unit area, including all wavelengths of electromagnetic radiation, that reaches the Earth's atmosphere. Typically shown in units of watts per square meter (W/m²).

UHI (Urban Heat Island): The tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: The U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations.

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3 Human influences on the climate

Chapter Summary

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. The vast majority of academic climate "impacts" studies in recent years are based upon the extreme RCP8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. Models disagree over the rate of land and ocean CO₂ uptake but all agree that it has been increasing since 1959.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean produce exchanges of energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the radiative heat it emits to space. Averaged over the Earth's surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth's energy balance at the top of the atmosphere are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

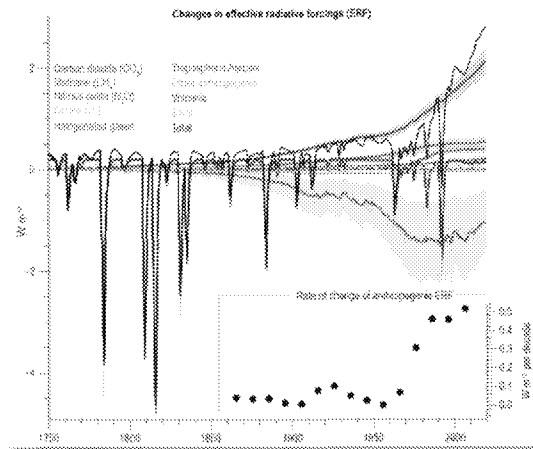


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Source: [HYPERLINK "<https://www.ipcc.ch/report/ar6/wg1/figures/chapter-2/figure-2-10/>"]

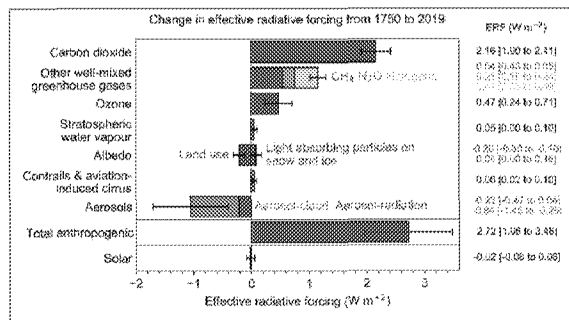


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: [HYPERLINK "<https://www.ipcc.ch/report/ar6/wg1/figures/chapter-7/figure-7-6/>"]

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of energy systems. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is increasing. Other greenhouse gases (methane, nitrous oxide,

halogens, and ozone) act similarly, currently adding another 75% to CO₂'s warming. Aerosols exert a cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of aerosols.

The IPCC views the change in the radiative forcing by the sun to be negligible, based on their preference for reconstructions that imply minimal solar change since preindustrial times. Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature covering the 1600-2000 interval; they vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th Century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. That prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta *et al.* 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 comes down to how the ACRIM data gap is filled. Connolly *et al.* (2023) found that the IPCC's consensus statements on solar forcing were prematurely formulated through the suppression of dissenting scientific opinions.

The other natural radiative forcing component is largely volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins *et al.* 2023, Schoeberl *et al.* 2024)

The anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m². Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends upon how much "extra" CO₂ accumulates in the atmosphere- i.e., its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at [HYPERLINK "<https://gml.noaa.gov/ccgg/trends/index.html>"]. The concentration was about 316 ppm at the start of the record in 1958 and is now about 415 ppm, a 32 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2 C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at CO₂ levels below 100 ppm, so if CO₂ levels had continued falling plant life might have been in peril.

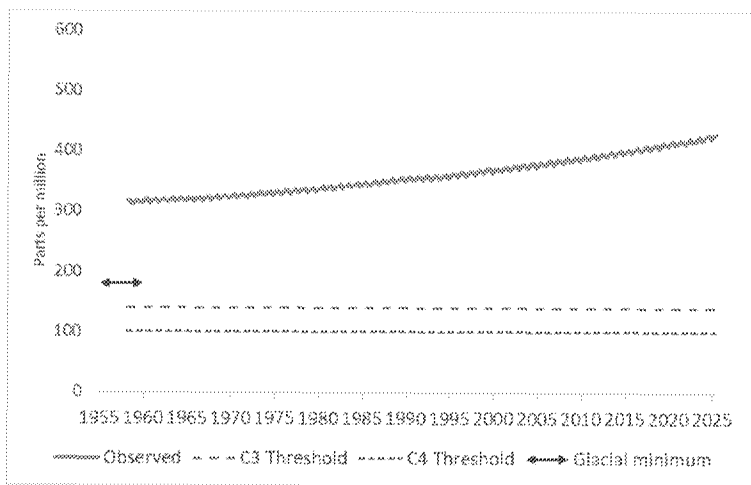


Fig 3.1.3. CO₂: Yearly average atmospheric CO₂ concentrations (1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: [HYPERLINK "<https://gml.noaa.gov/ccgg/trends/index.html>"]

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb "excess" CO₂ at a rate approximately 50% of the human emissions. Future concentrations, and hence future human influences on the

climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If they are not removed the data may over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures suffice for the purpose.

AR6 downplayed the issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10% in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10% upper bound without citing a source. AR4 (WGI p. 244) cited Jones et al. (1990) and Peterson et al. (1999) as the basis of the claim. Peterson et al. had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons and the relative influence of urbanization begins well below that (Spencer et al 2025). Jones et al. compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of "rural" included towns of up to 10,000 in the former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10% in these areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10% of the observed warming trend.

Prior to the IPCC AR4 several papers appeared in print arguing that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. The claim attracted controversy because it was presented with no supporting evidence. McKittrick (2010) and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. The AR5 (p. 189) conceded that the AR4 had provided "no explicit evidence" for its assessment and further acknowledged, based on these papers,

that there was "significant evidence for such contamination of the record" i.e. a warming bias in the land record. However as noted, elsewhere in the report they carried forward the AR4 claim that it was less than 10% of observed warming and they expressed no caution against using the land record for climate measurement on the assumption that it is not contaminated with UHI bias. Recently Soon et al. (2023) estimated an urbanization bias in the Northern Hemisphere land record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

Some studies providing evidence against UHI contamination compared warming rates between rural and urban locations (Jones et al. 1990, Peterson et al. 1999, Wickham et al. 2013). It is not known whether such methods would be capable of detecting UHI bias even when present. The influence of UHI warming is logarithmic, in other words it is strongest at low population growth levels then tapers off as local urbanization expands (Oke 1973, Spencer et al. 2025). Hence finding the same or more warming in rural areas than in nearby urban areas is consistent either with UHI bias being absent or present. McKittrick (2013) provided an empirical demonstration in which the rural/urban trends were not significantly different in a data set shown on other grounds to be contaminated with UHI bias.

Parker (2006) instead examined a sample of urban locations and found no difference in trends between subsets partitioned according to nighttime wind speed, concluding on this basis that urbanization could not be a significant factor. Here again the question is whether such a method would find UHI bias even if present. McKittrick (2013) presented an example in which UHI-contaminated data did not exhibit significant trend differences when stratified according to wind speed.

The challenge in measuring UHI bias is relating local temperature change to a corresponding change in population or urbanization, rather than to a static classification variable such as rural or urban. Spencer et al. (2025) use newly-available historical population archives to undertake such an analysis and found evidence of significant UHI bias in US summertime temperature data.

In summary while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases are not removed by the data processing algorithms used to produce climate data sets.

3.3 Future emissions scenarios and the carbon cycle

3.3.1 Emission scenarios

Because of the great uncertainties about these many factors in the decades to come, Assessing the dangers of future GHG emissions requires assumptions about what those

emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

Instead of making precise predictions of future concentrations, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a "6" corresponds to 6 W/m^2 of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m^2 .)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show a tendency for IPCC emission projections to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SRES scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SRES scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO_2 emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO_2 concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges.

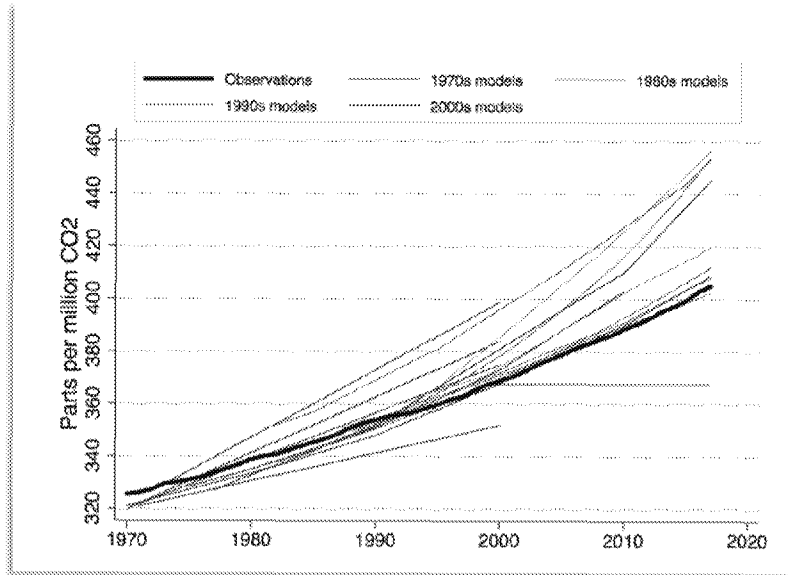


Figure 3.3.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather et al. (2019) Figure S4.

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) projects a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst-case,

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future.

and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are looking unlikely.

Widespread use of RCP8.5 has created an alarmist bias in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.3.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) merged with the emission projection from the EIA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP3 and higher.

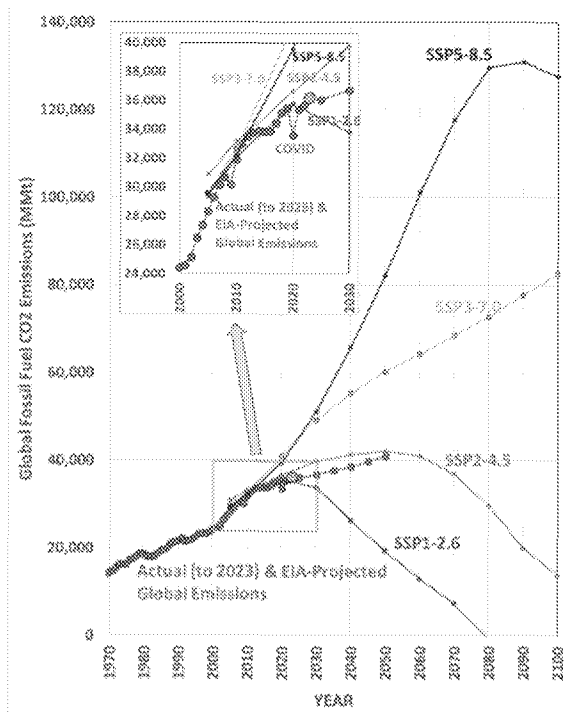


Figure 3.3.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5. Data source: Friedlingstein et al. (2024).

3.3.2 The carbon cycle relating emissions and concentrations

Carbon dioxide emissions from fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) have led to steadily increasing CO₂ concentrations in the atmosphere, as shown in Fig. 3.1.3. The relation between emissions and concentration is determined by the global carbon cycle models relate concentrations to emissions of using estimates of various land and ocean processes that exchange CO₂ carbon with the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021).

There are about 850 Gt of carbon (GtC) in the Earth's atmosphere², almost all of it in the form of CO₂. Each year, biological processes (plant growth and decay) and physical processes (ocean absorption and outgassing) exchange about 200 GtC of that carbon with the Earth's surface (roughly 80 GtC with the land and 120 GtC with the oceans). Before human activities became significant, removals from the atmosphere were roughly in balance with additions, as inferred from the near constancy of CO₂ levels in air bubbles trapped in ice cores. But burning fossil fuels (coal, oil, and gas) takes carbon out of the ground and adds it to the annual exchange. That addition (together with a much smaller contribution from cement manufacturing) amounted to 10.3 GtC in 2023, or only about 5 percent of the annual exchange.

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The carbon cycle accommodates humanity's small annual injection of carbon by ~~Of this, about half is naturally sequestering about 50 percent of it~~ through plant growth and oceanic uptake while the remainder ~~remains, about half, adds to the accumulates in the atmosphere is a stock~~ (Ciais et al. 2013).

The natural fluxes of CO₂ in and out of the Earth's surface are an order of magnitude larger than anthropogenic emissions, but the natural CO₂ sources and sinks were assumed to be in approximate balance in pre-industrial times, as inferred from relatively constant levels of atmospheric CO₂ found in air bubbles trapped in ice cores. This is one of several reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig. 3.1.3. CO₂ emissions from fossil fuel burning is a small fraction of the natural carbon cycle components. About 44,000 Gigatonnes of carbon equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂ (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). ~~Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock~~ (Ciais et al. 2013).

² Because CO₂ is chemically transformed through the course of the carbon cycle, it is more convenient to track atoms of carbon rather than molecules of CO₂. One gigatonne of carbon (GtC) is equivalent to about 3.7 Gt of CO₂.

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, for that reason, the annual increase in atmospheric CO₂ concentration is only about half of that naively expected from human emissions. Anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration.

To project future CO₂ concentrations in the atmosphere, and hence future human influences on the climate, it is important to know how the carbon cycle might change in the future. The historical near-constancy of that 50% fraction also means that the more CO₂ humanity has produced, the faster Nature removed it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Niño, La Niña, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in the 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

CO₂ uptake by land processes

The uptake of extra CO₂ from the atmosphere by land surface processes (as also inferred from global greening) has been modeled with 20 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). As seen in Fig. 3.3.3, all of those models agree that vegetation and soils have been sequestering carbon from the atmosphere. But we also see that the long-term trends over 1959 to 2023 (65 years) vary widely between models, by nearly a factor of 7. This demonstrates that there remains considerable uncertainty regarding how fast CO₂ from the atmosphere is being removed by land processes, which in turn translates into uncertainty regarding future atmospheric CO₂.

concentrations. Those uncertain future CO₂ concentrations then imply a source of uncertainty in climate model simulations of future climate change.

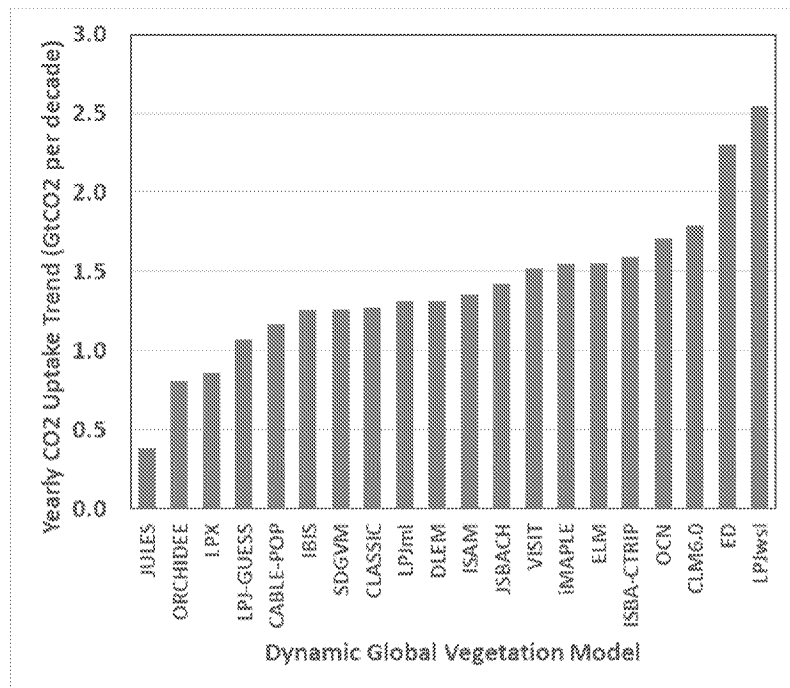


Figure 3.3.3 Decadal trends in the yearly CO₂ uptake by land processes during 1959-2023 simulated by 20 different dynamic global vegetation models periodically reported by the Global Carbon Project (Friedlingsstein, 2024).

CO₂ uptake by ocean processes

The uptake of extra CO₂ from the atmosphere by ocean processes has been modeled with 10 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingsstein, 2024). Like the results from the land models, all of the ocean models agree that the global oceans have been sequestering carbon from the atmosphere at an increasing rate during 1959-2023 (Fig. 3.3.4). Unlike the land models, however, the ocean models show much better agreement with each other, with the model producing the fastest increasing CO₂ uptake

being only 65% faster than the model with the most slowly increasing CO₂ uptake. Note that the average trend in CO₂ uptake across all land models in Fig. 3.3.3 is 25% larger than the average trend in ocean uptake. This suggests land processes are increasing in their ability to remove CO₂ faster than ocean processes are increasing their CO₂ sequestration.

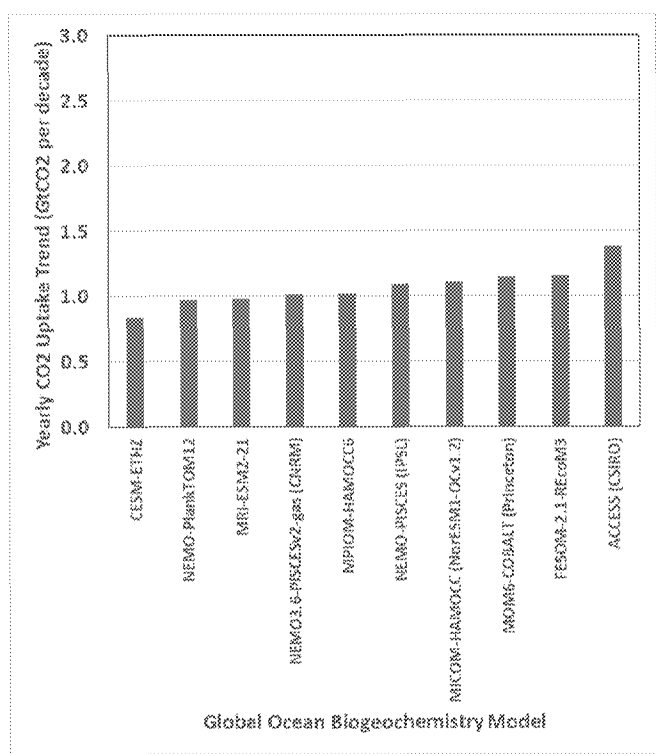


Figure 3.3.5 Decadal trends in the yearly CO₂ uptake by ocean processes during 1959-2023 simulated by 10 different ocean biogeochemistry models periodically reported by the Global Carbon Project (Friedlings et al., 2024).

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10 Managing Risks of Extreme Weather

10.1 Socioeconomic context

Risks from human-caused climate change are convoluted with natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020 (Goklany, 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population) (NOAA, 2025; USCB, 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang 2023). US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (NBER, 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA, 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (BMI, 2013). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages (APPA, 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (R Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster are down by about 80% since 1980, as a proportion of GDP. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from

publication (R Pielke Jr., 2025).

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period though not in the continental US (Chapter 6) and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao et al 2021, Ritchie 20214). Unlike with heat-related mortality, cold-weather risks set in even at moderately cold conditions (Gasparini et al. 2015, Lee and Dessler 2023). A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7% of deaths were attributable to sub-optimal temperatures, of which 7.4% were attributable to cold and only 0.4% were attributable to heat (Gasparini et al. 2015). In other words cold weather killed 18.5 times as many people as did hot weather.

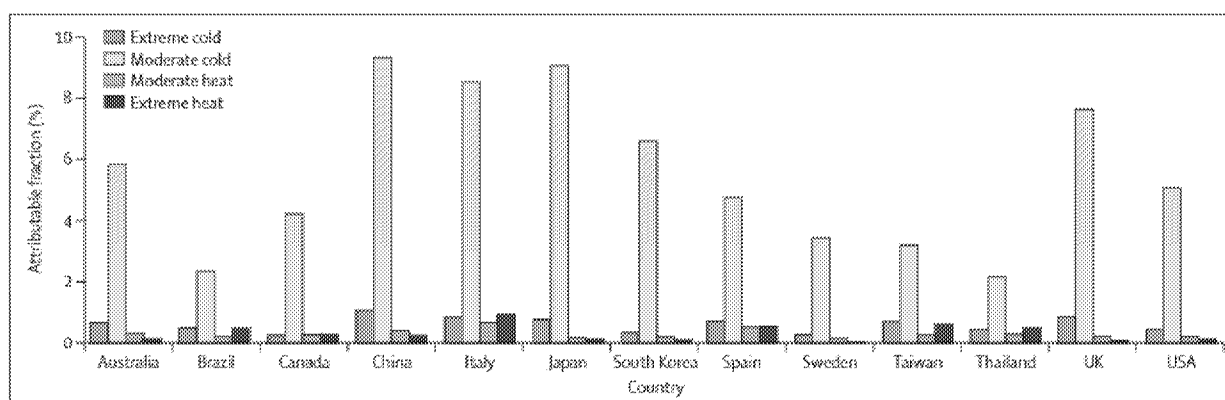


Figure 10.3.1. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini et al. (2015).

Figure 10.3.1 shows the distribution of results from Gasparini et al. (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9%, of which 5.5% was due to cold, thus cold weather killed 14 times as many people as hot weather.

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86% of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities

and found a 60% decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill et al. 2022) acknowledges that heat-related mortality risk is declining over time:

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

10.3.2 The importance of adaptation

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that

“Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

10.3.3 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through

conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels ($< 5^{\circ}\text{C}$) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days ($>30^{\circ}\text{C}$) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

10.4 Summary

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase as long as people are able to undertake adaptive responses.

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Global LT

	Sonde	Sonde	Sonde	Satellite	Satellite	Satellite	Reanalysis	Reanalysis
	RAOBCOR	RICH	RATPAC A	UAH_6.0	RSS	NOAA	ERA5	JRA3Q
1979	-0.360	-0.442	-0.414	-0.346	-0.495		-0.303	-0.405
1980	-0.213	-0.287	-0.275	-0.178	-0.344		-0.235	-0.303
1981	-0.240	-0.306	-0.282	-0.248	-0.358	-0.272	-0.261	-0.337
1982	-0.466	-0.530	-0.518	-0.433	-0.560	-0.393	-0.466	-0.481
1983	-0.267	-0.321	-0.362	-0.178	-0.327	-0.131	-0.235	-0.268
1984	-0.533	-0.586	-0.567	-0.374	-0.590	-0.402	-0.504	-0.547
1985	-0.493	-0.553	-0.530	-0.498	-0.645	-0.438	-0.535	-0.566
1986	-0.403	-0.481	-0.487	-0.356	-0.528	-0.274	-0.413	-0.430
1987	-0.125	-0.201	-0.242	-0.087	-0.233	0.033	-0.135	-0.130
1988	-0.112	-0.160	-0.196	-0.098	-0.264	0.012	-0.090	-0.105
1989	-0.373	-0.409	-0.446	-0.346	-0.467	-0.234	-0.318	-0.359
1990	-0.085	-0.113	-0.210	-0.124	-0.290	-0.015	-0.065	-0.119
1991	-0.083	-0.112	-0.245	-0.116	-0.245	0.006	-0.090	-0.130
1992	-0.414	-0.447	-0.512	-0.417	-0.518	-0.289	-0.376	-0.408
1993	-0.330	-0.366	-0.446	-0.339	-0.453	-0.275	-0.346	-0.392
1994	-0.266	-0.297	-0.293	-0.201	-0.318	-0.152	-0.255	-0.265
1995	-0.201	-0.227	-0.190	-0.067	-0.177	-0.053	-0.141	-0.146
1996	-0.324	-0.343	-0.369	-0.146	-0.278	-0.156	-0.246	-0.231
1997	-0.298	-0.316	-0.324	-0.144	-0.242	-0.159	-0.245	-0.228
1998	0.232	0.220	0.155	0.347	0.224	0.306	0.220	0.260
1999	-0.253	-0.259	-0.303	-0.153	-0.243	-0.211	-0.280	-0.215
2000	-0.284	-0.291	-0.326	-0.157	-0.248	-0.221	-0.315	-0.243
2001	-0.119	-0.137	-0.132	-0.022	-0.079	-0.061	-0.130	-0.063
2002	0.016	-0.006	-0.031	0.080	0.033	0.035	-0.001	0.033
2003	0.009	-0.008	0.024	0.050	0.048	0.014	-0.012	0.033
2004	-0.088	-0.091	-0.081	-0.056	-0.024	-0.088	-0.104	-0.049
2005	0.093	0.106	0.141	0.063	0.110	0.040	0.044	0.118
2006	-0.017	0.000	0.065	-0.023	0.020	-0.044	-0.035	0.018
2007	0.042	0.059	0.050	0.023	0.055	0.000	0.015	-0.005
2008	-0.254	-0.239	-0.199	-0.238	-0.153	-0.250	-0.240	-0.252
2009	-0.012	-0.001	0.013	-0.043	0.009	-0.043	-0.027	-0.049
2010	0.140	0.151	0.233	0.194	0.254	0.197	0.250	0.223
2011	-0.130	-0.115	-0.034	-0.120	-0.072	-0.109	-0.075	-0.071
2012	-0.059	-0.044	0.022	-0.084	-0.006	-0.084	-0.035	-0.036
2013	0.073	0.091	0.136	-0.001	0.069	0.004	0.068	0.058

2014	0.117	0.138	0.167	0.044	0.127	0.056	0.113	0.092
2015	0.270	0.287	0.302	0.137	0.260	0.154	0.221	0.197
2016	0.595	0.610	0.554	0.388	0.456	0.389	0.499	0.463
2017	0.355	0.373	0.382	0.265	0.332	0.240	0.359	0.307
2018	0.249	0.268	0.264	0.088	0.193	0.101	0.233	0.172
2019	0.470	0.492	0.481	0.296	0.401	0.293	0.437	0.368
2020	0.475	0.505	0.495	0.351	0.465	0.361	0.495	0.433
2021	0.238	0.275	0.298	0.138	0.271	0.184	0.290	0.234
2022	0.267	0.228	0.320	0.150	0.254	0.192	0.300	0.282
2023	0.515	0.530	0.573	0.432	0.551	0.475	0.585	0.571
2024	0.860	0.875	0.924	0.774	0.860	0.784	0.914	0.884
2025								
2026								
2027								
2028								
2029								
2030								

	ACCESS_C	ACCESS_E	AWI	BCC-CSM	CAMS	Can5	Can5-OE	CESM
1979	-0.190	-0.443	-0.313	-0.297	-0.210	-0.639	-0.613	0.026
1980	-0.269	-0.240	-0.356	-0.367	-0.092	-0.562	-0.634	0.047
1981	-0.193	-0.293	-0.293	-0.137	-0.159	-0.395	-0.552	-0.486
1982	-0.343	-0.479	-0.435	-0.123	-0.177	-0.262	-0.392	-0.469
1983	-0.458	-0.383	-0.433	-0.219	-0.178	-0.407	-0.596	-0.419
1984	-0.190	-0.292	-0.437	-0.179	-0.321	-0.464	-0.520	-0.373
1985	-0.130	-0.488	-0.268	-0.373	-0.522	-0.496	-0.186	0.052
1986	0.107	-0.458	-0.323	-0.263	-0.095	-0.465	-0.338	-0.263
1987	-0.319	-0.277	-0.140	-0.199	-0.017	-0.255	-0.359	-0.247
1988	-0.232	-0.328	-0.300	-0.190	-0.164	-0.237	-0.356	-0.079
1989	-0.130	-0.247	-0.040	0.002	0.056	-0.218	-0.037	-0.088
1990	0.036	-0.186	0.074	-0.049	0.142	-0.156	0.020	-0.167
1991	0.041	-0.261	-0.226	-0.263	0.014	-0.193	0.012	-0.257
1992	-0.517	-0.555	-0.545	-0.636	-0.397	-0.406	-0.595	-0.553
1993	-0.351	-0.325	-0.436	-0.377	-0.397	-0.559	-0.388	-0.270
1994	-0.178	-0.450	-0.198	-0.121	-0.168	-0.278	-0.452	0.034
1995	-0.193	-0.235	0.061	0.097	-0.060	-0.199	-0.224	-0.208
1996	-0.040	0.012	0.128	-0.258	-0.094	-0.038	0.166	-0.073
1997	-0.047	-0.014	-0.096	0.134	0.160	0.138	-0.003	0.183
1998	-0.029	0.206	-0.006	-0.028	0.247	0.197	-0.068	-0.111
1999	0.101	0.343	-0.020	-0.010	-0.019	0.333	0.128	0.069
2000	0.300	0.257	0.228	0.173	0.053	0.277	0.277	0.134
2001	0.199	0.458	0.272	0.324	-0.013	0.263	0.503	-0.051
2002	0.173	0.613	0.207	0.385	0.195	0.349	0.547	0.130
2003	0.366	0.393	0.368	0.309	0.318	0.387	0.464	0.442
2004	0.289	0.478	0.386	0.201	0.348	0.319	0.411	0.516
2005	0.334	0.443	0.228	0.300	0.371	0.405	0.306	0.335
2006	0.388	0.412	0.238	0.282	0.319	0.193	0.132	0.208
2007	0.097	0.231	0.406	0.307	0.287	0.306	0.326	0.327
2008	0.229	0.405	0.536	0.245	0.102	0.360	0.730	0.404
2009	0.238	0.493	0.485	0.342	0.093	0.552	0.486	0.524
2010	0.441	0.529	0.593	0.310	0.082	0.943	0.549	0.743
2011	0.555	0.550	0.352	0.326	0.231	0.878	0.577	0.858
2012	0.762	0.469	0.459	0.374	0.250	0.608	0.791	0.452
2013	0.387	0.666	0.551	0.443	0.498	0.807	0.586	0.500

2014	0.542	0.756	0.491	0.510	0.398	0.956	0.814	0.697
2015	0.789	0.744	0.450	0.484	0.400	0.812	0.865	0.610
2016	0.588	0.663	0.617	0.466	0.560	0.754	0.960	0.659
2017	0.743	0.832	0.716	0.608	0.353	1.030	0.862	0.841
2018	0.928	0.858	0.727	0.630	0.467	0.945	0.852	0.661
2019	0.778	0.656	0.773	0.506	0.562	0.875	1.173	0.613
2020	0.868	0.621	0.579	0.673	0.600	1.237	1.105	0.656
2021	0.864	0.561	0.817	0.694	0.811	1.107	1.291	0.599
2022	1.081	0.832	0.940	0.734	0.691	1.087	1.221	0.796
2023	0.952	0.906	0.961	0.791	0.397	1.237	1.275	1.226
2024	1.101	1.064	0.956	0.680	0.449	1.293	1.265	1.034
2025	1.176	0.961	0.908	0.637	0.680	1.497	1.475	1.173
2026	1.096	1.221	0.954	0.953	0.462	1.794	1.604	1.253
2027	1.271	1.319	0.900	0.940	0.657	1.622	1.507	0.679
2028	1.357	1.294	0.967	1.031	0.458	1.517	1.544	0.991
2029	1.352	1.426	1.002	0.925	0.303	1.465	1.785	1.064
2030	1.274	1.257	1.039	1.004	0.283	1.477	1.624	1.224

CESM2-W	CIESM	CIESM	CNRM-CN	CNRM_HI	CNRM-ES	EC-EARTH	EC-E3-VE	FGOALS-f	FGOALS-g
-0.288	-0.434	-0.250	-0.334	-0.282	-0.153	-0.018	-0.453	-0.416	-0.399
-0.459	-0.277	-0.048	-0.117	-0.232	-0.238	0.112	-0.262	-0.130	-0.158
-0.093	-0.155	-0.030	-0.194	-0.175	-0.339	-0.288	0.028	-0.151	-0.198
-0.222	-0.428	-0.246	-0.335	-0.051	-0.282	-0.372	-0.396	-0.395	-0.273
-0.554	-0.561	-0.169	-0.200	-0.421	-0.171	-0.472	-0.484	-0.290	-0.410
-0.285	-0.254	-0.125	-0.357	-0.389	-0.274	-0.058	-0.293	-0.217	-0.392
-0.325	-0.060	-0.298	-0.261	-0.175	-0.269	-0.416	-0.333	-0.622	-0.305
-0.501	-0.357	-0.406	-0.288	-0.330	0.001	-0.476	-0.273	-0.218	-0.497
-0.471	-0.231	-0.181	-0.048	-0.188	-0.191	-0.311	-0.335	-0.076	-0.108
-0.132	-0.083	-0.104	-0.037	-0.157	-0.061	-0.107	-0.328	-0.344	0.005
-0.038	-0.148	-0.148	-0.110	-0.053	-0.238	0.117	-0.174	-0.184	-0.197
-0.223	0.046	-0.047	0.023	-0.046	-0.165	0.205	-0.005	0.206	-0.064
-0.323	0.111	0.166	-0.056	-0.061	0.077	-0.163	0.215	-0.250	0.052
-0.199	-0.454	-0.454	-0.236	-0.209	-0.192	-0.755	-0.570	-0.547	-0.633
-0.147	-0.455	-0.433	-0.006	-0.145	-0.255	-0.663	-0.530	-0.057	-0.481
-0.158	-0.172	-0.550	-0.369	-0.028	0.176	-0.346	-0.214	-0.015	-0.158
-0.122	0.079	-0.463	-0.210	-0.062	-0.111	0.105	-0.134	-0.147	-0.301
-0.131	-0.151	-0.273	0.114	-0.023	-0.031	-0.255	0.058	0.026	-0.115
-0.024	0.015	-0.164	-0.183	0.063	0.116	-0.144	0.213	0.145	0.220
-0.089	0.185	-0.096	0.077	0.003	-0.146	0.007	0.315	0.110	0.024
0.046	0.249	-0.077	0.119	0.115	0.158	0.183	0.082	0.187	0.093
0.275	0.033	-0.031	0.241	-0.010	0.043	0.272	0.051	0.074	0.232
0.498	0.186	0.185	0.335	0.077	0.017	0.258	0.285	0.110	0.112
0.420	0.372	0.445	0.263	0.152	0.053	0.241	0.279	0.416	0.347
0.407	0.117	0.542	0.166	0.262	0.249	0.277	0.345	0.122	0.356
0.319	0.155	0.241	0.353	0.120	0.037	0.204	0.435	0.387	0.451
0.247	0.405	0.197	-0.058	0.251	0.310	0.639	0.262	0.513	0.395
0.211	0.546	0.357	0.137	0.142	0.074	0.687	0.345	-0.057	0.324
0.498	0.245	0.537	0.501	0.300	0.522	0.301	0.415	0.306	0.357
0.488	0.155	0.633	0.316	0.285	0.390	0.296	0.290	0.672	0.311
0.252	0.252	0.543	0.130	0.300	0.096	0.377	0.187	0.085	0.487
0.380	0.371	0.441	0.181	0.450	0.402	0.645	0.268	0.201	0.356
0.550	0.262	0.502	0.311	0.301	0.489	0.413	0.382	0.537	0.381
0.672	0.338	0.597	0.487	0.425	0.330	0.497	0.574	0.357	0.524
0.508	0.551	0.670	0.306	0.379	0.560	0.606	0.440	0.462	0.234

0.537	0.604	0.466	0.415	0.434	0.530	0.786	0.545	0.626	0.518
0.707	0.218	0.616	0.420	0.530	0.459	0.393	0.594	0.372	0.235
0.857	0.256	0.928	0.590	0.406	0.705	0.525	0.606	0.514	0.778
0.845	0.563	0.989	0.706	0.519	0.593	0.402	0.686	0.457	0.781
0.957	0.680	0.242	0.377	0.725	0.668	0.671	0.798	0.523	0.772
0.582	0.625	0.033	0.532	0.654	0.866	0.770	0.908	0.885	0.785
0.489	0.561	0.009	0.767	0.605	0.684	0.459	0.923	0.730	0.632
0.927	0.687	0.488	0.722	0.621	0.825	0.575	0.694	0.549	0.505
1.044	0.739	0.820	0.849	0.747	0.594	0.808	0.674	1.009	0.664
0.772	0.853	0.697	0.746	0.807	0.952	0.609	0.745	1.018	0.607
0.933	0.633	0.706	0.829	0.968	1.165	0.744	0.913	0.633	0.957
1.181	0.816	0.616	0.978	0.530	0.970	0.835	1.019	1.024	0.748
1.092	1.064	0.679	0.783	0.406	1.090	0.850	0.724	1.161	0.852
1.027	0.967	0.856	0.923	0.519	1.039	0.723	0.833	0.689	0.751
1.268	1.113	1.047	1.127	0.725	1.228	0.717	0.867	0.948	0.681
1.467	1.101	0.924	0.767	0.654	0.930	0.827	0.957	1.190	0.944
1.062	1.127	0.859	0.909	0.605	1.183	0.993	1.057	0.929	0.783

FIO	GFDL-CM	GFDL-ESM	GISS	HadGEM	IITM	INM-CM4	INM-CM5	IPSL-CM6	KACE
-0.498	-0.173	-0.194	0.009	-0.460	-0.199	-0.148	-0.136	-0.296	-0.472
-0.409	-0.212	-0.394	-0.077	-0.349	-0.308	-0.197	-0.104	-0.195	-0.321
-0.363	-0.538	-0.187	-0.289	-0.456	-0.273	-0.187	-0.237	-0.178	-0.207
-0.488	-0.322	0.057	-0.412	-0.350	-0.214	-0.245	-0.208	-0.569	-0.403
-0.600	-0.359	-0.389	-0.089	-0.497	-0.296	-0.667	-0.636	-0.695	-0.487
-0.267	-0.369	-0.440	0.013	-0.248	-0.092	-0.398	-0.458	-0.509	-0.239
-0.148	-0.504	-0.419	-0.425	-0.392	-0.322	-0.264	-0.401	-0.653	-0.363
-0.399	-0.250	-0.228	-0.572	-0.264	-0.171	-0.218	-0.195	-0.378	-0.216
-0.193	0.053	-0.234	-0.325	-0.345	0.036	-0.232	-0.213	-0.039	-0.193
-0.098	-0.104	-0.298	0.137	-0.303	-0.016	-0.120	-0.129	0.136	-0.024
-0.029	-0.079	-0.156	0.263	-0.227	-0.154	-0.026	-0.013	0.405	-0.150
0.184	-0.113	0.211	0.147	-0.047	0.010	0.069	0.001	-0.121	0.020
0.020	-0.135	0.144	-0.147	0.001	0.092	0.056	0.084	-0.278	-0.146
-0.289	-0.410	-0.635	-0.652	-0.336	-0.382	-0.461	-0.386	-0.342	-0.403
-0.307	-0.396	-0.554	-0.344	-0.377	-0.163	-0.468	-0.459	-0.340	-0.338
-0.301	-0.376	-0.118	0.166	-0.384	-0.280	-0.274	-0.237	-0.138	-0.174
-0.154	-0.217	-0.118	-0.111	-0.248	-0.143	-0.057	-0.091	-0.001	-0.141
-0.021	-0.063	-0.126	-0.390	-0.119	-0.110	0.021	-0.035	0.125	-0.064
-0.007	0.124	0.002	-0.091	-0.041	-0.106	0.078	0.116	0.139	0.027
0.061	0.105	0.027	0.212	0.023	-0.040	0.106	0.153	-0.048	0.021
0.119	-0.034	0.166	0.287	0.011	0.100	0.210	0.151	0.056	0.130
0.237	0.258	0.222	-0.142	0.122	0.241	0.268	0.191	0.268	0.065
0.393	0.331	0.322	-0.182	0.315	0.313	0.246	0.193	0.181	0.130
0.126	0.232	0.365	0.210	0.439	0.108	0.139	0.250	0.113	0.270
0.148	0.236	0.195	0.279	0.265	0.310	0.272	0.319	0.105	0.341
0.238	0.459	0.349	0.037	0.423	0.283	0.336	0.371	0.083	0.355
0.422	0.333	0.300	-0.010	0.405	0.369	0.273	0.323	0.435	0.324
0.369	0.447	0.109	0.289	0.614	0.235	0.253	0.326	0.497	0.243
0.333	0.479	0.213	0.623	0.542	0.362	0.261	0.325	0.176	0.351
0.300	0.469	0.352	0.569	0.305	-0.037	0.270	0.277	0.126	0.384
0.346	0.270	0.506	0.575	0.476	0.102	0.339	0.354	0.635	0.421
0.362	0.479	0.348	0.374	0.685	0.246	0.425	0.277	0.822	0.453
0.434	0.632	0.348	0.217	0.910	0.349	0.387	0.258	0.324	0.492
0.397	0.565	0.578	0.468	0.831	0.466	0.384	0.319	0.595	0.494
0.227	0.531	0.799	0.526	0.637	0.201	0.461	0.346	0.634	0.451

0.367	0.672	0.381	-0.041	0.886	0.372	0.352	0.309	0.378	0.579
0.476	0.763	0.379	0.026	0.968	0.427	0.379	0.454	0.340	0.768
0.612	0.666	0.576	0.566	1.007	0.594	0.356	0.469	0.442	0.778
0.546	0.529	0.777	0.813	0.945	0.278	0.425	0.432	0.812	0.967
0.650	0.625	0.902	0.422	1.067	0.445	0.356	0.397	0.874	0.864
0.853	0.645	0.990	0.154	0.989	0.597	0.461	0.502	0.627	1.002
0.681	0.740	0.499	0.410	1.075	0.336	0.544	0.459	0.758	1.003
0.837	0.757	0.579	0.943	1.242	0.522	0.606	0.634	0.836	1.197
0.767	0.975	0.796	0.916	1.536	0.533	0.595	0.676	0.591	1.233
0.824	0.926	0.968	0.862	1.348	0.199	0.603	0.600	0.716	1.240
0.655	0.923	0.977	0.682	1.385	0.517	0.842	0.755	0.960	1.302
0.730	1.018	0.861	1.069	1.503	0.636	0.799	0.700	1.029	1.396
0.968	1.196	1.057	1.206	1.541	0.938	0.830	0.703	1.184	1.410
0.948	1.047	0.904	0.659	1.544	0.507	0.788	0.746	1.036	1.431
1.000	1.080	0.844	0.338	1.626	0.779	0.799	0.858	0.931	1.493
0.928	1.219	0.864	0.681	1.627	0.704	0.820	0.808	0.996	1.498
0.925	1.354	1.065	1.170	1.504	0.566	0.823	0.924	0.810	1.498

KIOST	MCM-UA	MIROC6	MIROC6-2	MPI-HR	MPI-LR	MRI-ESM	NESM	NOR-LM	UKESM1
-0.248	-0.458	-0.170	-0.287	-0.274	-0.439	-0.237	-0.287	-0.450	-0.480
-0.488	-0.397	-0.410	0.019	0.043	-0.117	-0.366	-0.346	-0.285	-0.564
-0.348	-0.394	-0.475	0.161	-0.085	-0.178	-0.174	-0.221	-0.261	-0.433
-0.286	-0.452	-0.146	-0.458	-0.238	-0.351	-0.131	-0.217	-0.127	-0.390
-0.406	-0.557	-0.131	-0.626	-0.394	-0.466	-0.265	-0.733	-0.065	-0.484
-0.533	-0.327	0.191	-0.312	-0.309	-0.174	-0.407	-0.377	-0.203	-0.398
-0.323	-0.265	-0.097	0.112	-0.143	-0.062	-0.053	-0.503	-0.333	-0.508
-0.268	-0.290	-0.432	0.188	0.076	-0.030	-0.049	-0.407	-0.186	-0.314
-0.189	-0.312	-0.176	-0.371	0.001	-0.223	-0.213	-0.321	-0.384	-0.303
0.127	-0.190	-0.045	-0.373	-0.023	-0.306	-0.009	-0.159	-0.395	-0.437
-0.144	-0.262	-0.158	-0.231	-0.084	-0.205	-0.235	0.046	-0.163	-0.184
0.012	-0.178	-0.129	0.093	-0.018	0.004	-0.178	0.203	-0.074	-0.004
0.246	-0.285	-0.165	0.412	-0.164	0.020	-0.021	0.007	0.038	-0.260
-0.682	-0.397	-0.455	-0.530	-0.497	-0.406	-0.453	-0.569	-0.338	-0.698
-0.233	-0.301	-0.177	-0.713	-0.408	-0.136	-0.277	-0.514	-0.490	-0.434
-0.379	-0.248	0.128	-0.378	-0.064	-0.213	-0.212	-0.128	-0.367	-0.090
-0.181	-0.214	-0.307	-0.021	0.025	-0.339	-0.023	-0.161	-0.198	-0.128
-0.010	0.075	-0.474	0.168	-0.078	-0.064	-0.223	-0.045	-0.047	-0.082
-0.263	0.279	-0.210	0.383	-0.247	0.250	-0.097	-0.033	0.120	0.028
0.073	0.250	-0.076	-0.219	-0.023	0.127	0.111	0.202	0.205	0.288
0.176	0.280	0.416	-0.321	0.066	0.146	0.005	0.379	0.276	0.218
0.132	0.396	0.252	-0.070	0.087	0.107	0.093	0.214	0.446	0.252
0.372	0.252	0.086	0.384	0.251	0.035	0.331	0.061	0.529	0.305
0.012	0.220	-0.015	0.200	0.315	0.090	0.057	0.361	0.023	0.548
0.183	0.402	0.306	0.122	0.142	0.391	0.049	0.418	-0.032	0.263
0.380	0.637	0.628	0.659	0.109	0.319	0.200	0.325	0.171	0.313
0.338	0.618	0.211	0.658	0.117	0.107	0.520	0.263	0.145	0.417
0.217	0.185	0.049	-0.054	0.240	0.135	0.332	0.405	0.044	0.450
0.287	0.298	0.101	-0.115	0.176	0.329	0.319	0.326	0.248	0.478
0.664	0.332	0.537	0.156	0.356	0.451	0.451	0.443	0.460	0.467
0.646	0.257	0.690	0.324	0.461	0.319	0.339	0.395	0.502	0.517
0.371	0.180	0.062	0.773	0.340	0.325	0.201	0.334	0.445	0.596
0.708	0.329	0.039	0.383	0.416	0.390	0.194	0.683	0.593	0.642
0.803	0.654	0.240	0.164	0.521	0.437	0.380	0.780	0.484	0.615
0.664	0.744	0.799	0.265	0.598	0.293	0.412	0.885	0.592	0.687

0.813	0.731	0.724	0.519	0.494	0.275	0.338	0.522	0.870	0.826
0.613	0.895	0.044	0.894	0.312	0.400	0.522	0.912	0.597	0.797
0.409	0.856	-0.057	0.283	0.345	0.527	0.628	0.839	0.508	0.982
0.484	0.629	0.314	0.177	0.282	0.529	0.851	0.822	0.593	0.840
0.373	0.403	0.762	0.387	0.493	0.403	0.519	0.879	0.728	0.841
0.687	0.337	0.353	0.707	0.747	0.171	0.475	0.954	0.923	1.051
0.472	0.468	0.236	1.063	0.674	0.360	0.593	1.031	0.873	1.140
0.838	0.695	0.289	0.650	0.714	0.815	0.677	1.347	0.746	0.867
0.593	0.815	0.423	0.879	0.815	0.607	1.008	1.201	0.948	1.120
0.773	0.700	0.676	1.281	0.632	0.573	1.040	1.275	0.634	1.348
0.996	0.653	1.004	0.884	0.788	0.840	0.896	1.372	0.511	1.304
0.537	0.909	0.513	0.479	0.838	0.608	0.910	1.490	0.531	1.444
0.923	0.904	0.500	0.516	0.514	0.556	1.050	1.229	0.396	1.381
1.010	0.851	0.674	0.733	0.560	0.532	1.078	1.097	0.431	1.376
0.777	0.828	1.041	1.100	0.678	0.711	1.088	0.962	0.789	1.422
1.041	0.909	1.293	1.289	0.952	0.795	1.187	1.235	0.998	1.558
0.979	1.085	0.602	0.629	0.795	0.950	0.943	1.201	0.986	1.579

2 CO₂ fertilization and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1 CO₂ and global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

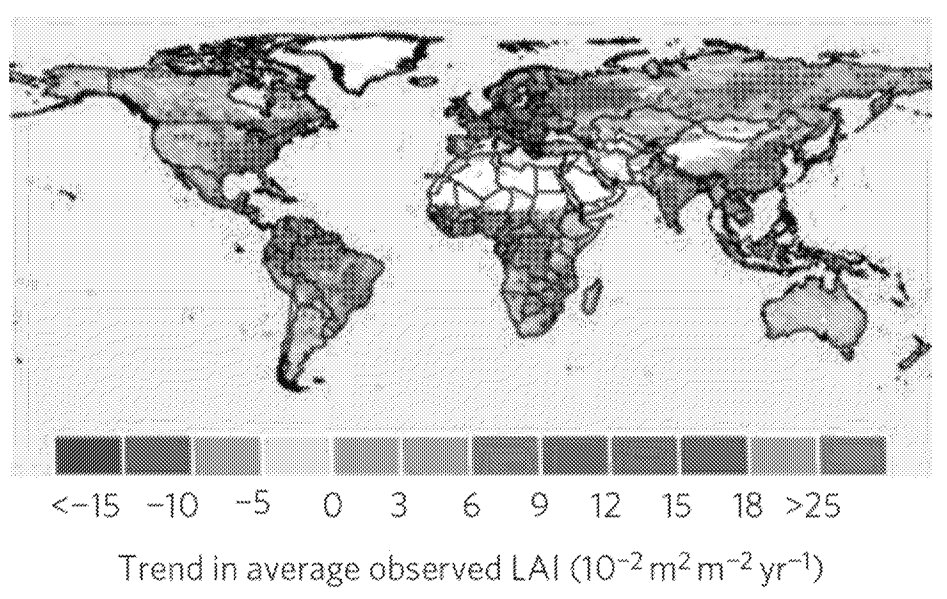


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

Commented [TF1]: I got stuck on this word. Do we mean something more like “accelerating” or “enhancing”?

While plant models predict increases in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver.

2.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth's atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

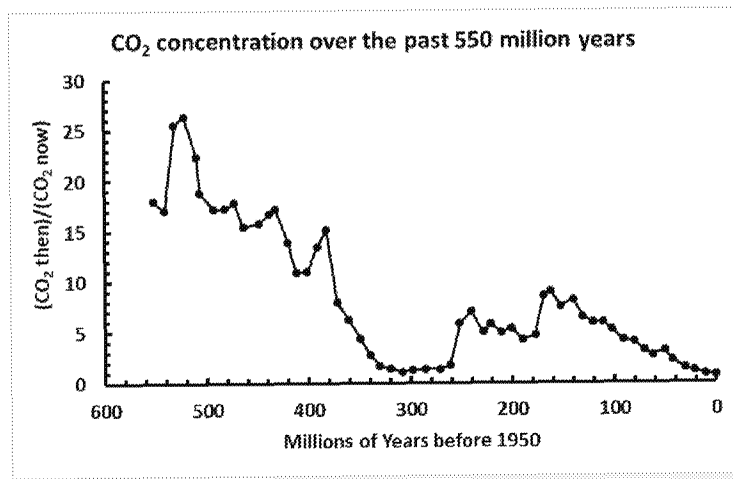


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels.
Source: Berner (2006)

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024).

Commented [TF2]: This chart took a minute to digest. Once I understood what was going on, I still wasn't sure what year (or CO₂ concentration) was being used for "CO₂ now." Is it the 1950 level or something more recent?

My suggestion would be to show this in terms of PPM and clarify what "CO₂ now" means.

Commented [TF3R2]: It's no problem to keep as-is if we would have to redo the whole thing, especially if we don't have the underlying data. I just want to flag things that strike me as less than straightforward.

Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

Commented [TF4]: I know we probably don't want to alter these images, but should we add a label that says "(2010)" under the "Current 350 ppm" plant in the image? We are moving past the 420-425 ppm range presently, right?

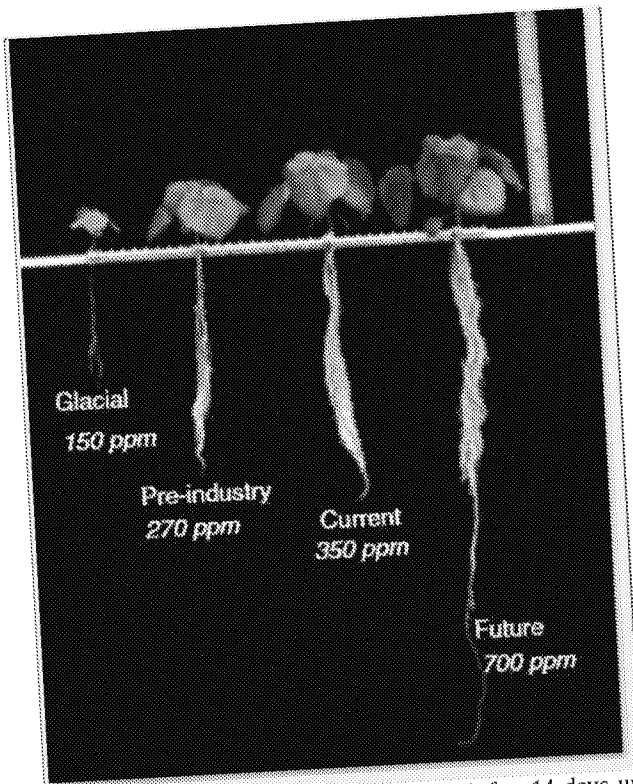


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

Rising CO₂ and crop water use efficiency

Deryn et al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Deryn et al. (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryn et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.3 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening and CO₂ fertilization of agricultural crops.

Commented [TF5]: I feel as confident as you all that this statement is true, but its tone is borderline acerbic. To be clear, I see no harm in adding some occasional spice, but I wanted to flag it for your consideration.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

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5.8 Hemispheric symmetry of the planetary Earth's albedo

The planetary albedo is the portion-fraction of solar radiation reflected by the planet Earth back to space, and is an important determinant-component of the radiative balance and hence whether the planet will warm or cool over time. An intriguing property of the planetary Earth's albedo is that, on average, the Northern Hemisphere (NH) and Southern Hemisphere (SH) have had very nearly the same albedo (Stephens et al., 2015). The hemispheric symmetry is at least robust throughout the fifty-year satellite record (Stephens et al., 2015) (since the 1970s). This symmetry of the hemispheric albedo is surprising, because the SH has much more ocean than land. Since, and ocean is less reflective than land, so the NH should have higher albedo. Clouds (which are highly reflective) are more common in the NH, and so compensate the surface albedo imbalances of the two hemispheres, leading to an overall symmetric albedo between the hemispheres. Datseris and Stephens (2021) show that this cloud compensation comes from the extra-tropical storm tracks of the SH, which are cloudier than those of the NH.

While the mechanism reasons for this hemispheric symmetry in albedo are unclear, its mechanism likely operates on large temporal and spatial scales.

The existence of this symmetry The hemispheric symmetry of the albedo is a simple useful-gross metric for evaluating climate models. Rugenstein and Hakuba (2023) defined that metric as the difference between the NH and SH annual mean albedos, expressed as Wm^{-2} evaluate the hemispheric albedo of the reflected sunlight, and compiled it for the CMIP6 climate models-simulations, as shown in Figure 5.8.1. Most of the CMIP6 models do not reproduce the small observed asymmetry (about 0.1 Wm^{-2}). Albedo asymmetry is defined by the NH minus the SH the Northern Hemisphere (NH) minus Southern Hemisphere (SH) difference in annual mean hemispheric albedo. The observed asymmetry is small, about 0.1 Wm^{-2} . Figure 5.8.1 shows that the observed hemispheric symmetry of reflected flux is not reproduced by most of the CMIP6 models, and even there is disagreement between models as to which hemisphere is more reflective. Moreover, the magnitude of the asymmetry ranges up to 5 Wm^{-2} in some of the models, is very twice as large as the current anthropogenic forcing, large, compared both to the observed value and to current human influences (about 2.5 Wm^{-2}).

The significance of unphysical this discrepancy albedo asymmetries between in the climate models and observations of the hemispheric albedo symmetry is not yet fully known. However, other model studies suggest that interhemispheric changes in albedo can alter the amount of poleward heat fluxes, heat moved poleward, meridional temperature gradients, storminess, and differences in hemispheric ocean heat storage. The discrepancy between models and observations further raises issues regarding cloud feedback processes and so more generally diminishes confidence in model projections of the future climate and their magnitude.

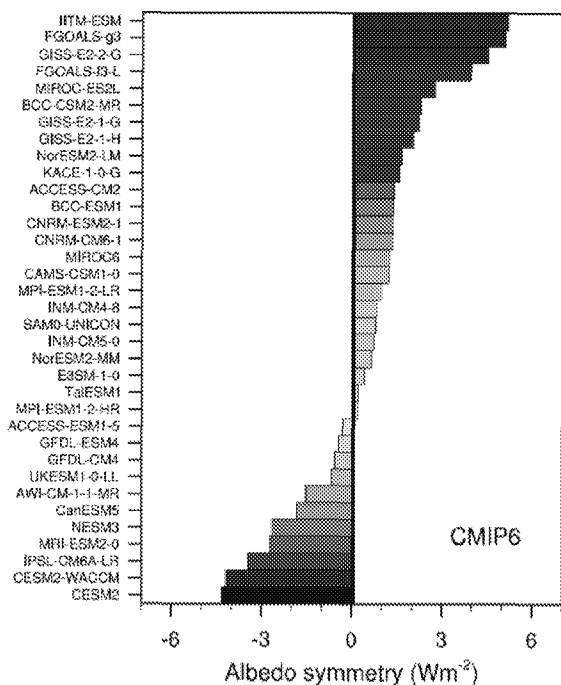


Figure 5.8.1 Differences in the reflectivity (albedo) between the Northern and Southern Hemispheres for CMIP6 models used in the most recent IPCC assessment (colored bars). The very small observed difference is indicated by the vertical black line. From Rugenstein and Hakuba (2023).

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GLOSSARY

2XCO₂: doubling of the atmospheric CO₂ content relative to pre-Industrial times, a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50% of the way to 2XCO₂.

ABATEMENT: ~~in the context of environmental policy the in the context of pollution, the reduction of harmful impacts through pollution reductions~~
reduction of emissions

ACE (Accumulated Cyclone Energy): a statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds

ACIDIFICATION: a commonly used term for the reduction in ocean pH from more alkaline to less alkaline values

AEROSOLS: tiny solid or liquid particles suspended in the air

ALKALINE: having a chemical pH greater than 7.0. The "opposite" of acidic, which means a pH less than 7.0

AMBIENT: relating to the immediate surroundings of something

ANTHROPOGENIC: created by humans

AR (IPCC Assessment Reports): periodic assessments published by the IPCC evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science. The most recent was the AR6 in 2023.

ATTRIBUTION: assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: the phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: the total quantity or weight of organic matter in a given area or volume

CARBON: ~~The 6th element in the periodic table. popular and widely~~ Popularly used as a shorthand term for carbon dioxide

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CMIP (Coupled Model Intercomparison Project): The IPCC's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CONUS: the contiguous 48 U.S. states

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model (IAM) developed by William Nordhaus in 1993.

DISCOUNT RATE: ~~here, the~~ The interest rate used to convert future costs and benefits of environmental regulations into their present value. ~~Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits environmental benefits from regulating sooner; a low discount rate favors long-term benefits of regulating sooner.~~

DRY ICE: frozen carbon dioxide

ECONOMETRICS: the branch of economics concerned with the use of ~~math and statistics~~ statistical methods (chiefly multiple regression) in describing and analyzing economic systems

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: the warm phase of ENSO, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): the 2009 finding by the Administrator of the EPA that CO₂ emissions endanger human health and welfare

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean

FACE: (Free-Air CO₂ Enrichment) large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: a natural hydrocarbon fuel such as coal or natural gas formed in the geological past from the remains of living organisms

FUND: An Integrated Assessment Model (IAM) developed by Richard Tol in 1997.

GBR (Great Barrier Reef): the world's largest coral reef ecosystem located off the northeast coast of Australia

GDP (Gross Domestic Product): total market value of all the final goods and services produced within a country's border, usually over one year

GHCN: the Global Historical Climatology Network, consisting of a time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: the satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s

GNP (Gross National Product): total market value of all the final goods and services produced by the citizens a country, usually over one year

GREENHOUSE EFFECT (GHE): the tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): an atmospheric gas that absorbs and emits infrared (IR) radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: see long term persistence.

HYDROLOGY: the study of the movement of water, especially on land and the atmosphere

IAM (Integrated Assessment Model): a computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions

IEA: International Energy Agency

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies

IR (Infrared): heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: the cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): the tendency for natural systems such as precipitation, droughts, and floods to have persisting behavior over time, as opposed to random behavior, which impacts our interpretation of long term trends in climate data a form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales

MAIZE: corn

MODEL: a computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes

MORTALITY: death or number of deaths, usually expressed for a specific population and period

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States> There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023)

OECD (Organization for Economic Cooperation and Development): a specific list of 38 countries having a democratic system of government and free economics systems

PALEOCLIMATE: climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): a statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds

PHOTOSYNTHESIS: the process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function)

PPM: parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: the historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s

RADIATIVE FEEDBACK: a change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature

RADIATIVE FORCING: the change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP SCENARIOS: Representative Concentration Pathways, different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC’s Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they assume in 2100 relative to pre-Industrial times, in Watts per sq. meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: a method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SOCIAL COST OF CARBON (SCC): an estimate of the total economic damages, measured in dollars, caused by emitting one additional ton of CO₂ into the atmosphere

SSP SCENARIOS: Shared Socioeconomic Pathways, different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC’s Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: tropical cyclone

TMAX: the daily maximum surface air temperature

TMIN: the daily minimum surface air temperature

TOA: top of atmosphere

TOXICOLOGY: the study of the adverse effects of chemical substances on living organisms.

TREND: usually, the coefficient, usually estimated using linear regression, representing the slope of a line of best fit-linear regression slope fit to a time series of data, one of the most commonly used metrics to describe climate change over a long period of time through a time series of data, indicating any tendency for the series mean to move up or down over time.

UHI (Urban Heat Island): the tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: the U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations

12.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly melting glaciers and increasing average temperature, are gradual changes caused by steady warming. A important driver of potentially high values of the Social Cost of Carbon (SCC) is the likelihood introduction into models of discrete catastrophic outcomes, which may be associated with abrupt changes (Dietz et al. 2021). In this context, catastrophic outcomes are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen et al. 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily depend on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford 1991).

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The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the latter is a possibility. Kypke et al. (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon 2023).

The possible existence of bifurcations in the Earth’s climate system implies abrupt transitions are possible, not just in response to large forcing but to small perturbations as well. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos et al 2024) and indeed may not be able to since one implication of the “butterfly effect” is the existence of predictability boundaries of nonlinear systems (Palmer et al. 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict or prevent it from happening.

The IPCC AR6 (Chapter 1) defines focuses mainly on the first type of a tipping point, namely as an abrupt change that occurs because the system state becomes unstable in response to external forcing. This is also the meaning associated with popular usage of the “tipping point” concept in discussions of climate change (see [HYPERLINK "https://report-2023.global-tipping-points.org/what-is-a-tipping-point/"] for example), so that the subsequent rate of change is independent of the external forcing. The AR6 distinguishes between two types of tipping points: noise-induced tipping points that are induced by extreme climate events, and bifurcation tipping points that are associated with system instability. Noise-induced tipping events develop from fluctuations within the system.

Bifurcation tipping from one state to another can occur if a critical threshold is exceeded. The new state is defined as irreversible in this context if the recovery from the new state takes substantially longer than decades to centuries. In other words, tipping points are points of no return, at least on the century timescale. Tipping point events could induce severe responses for aspects of either the global climate or regional climate.

As summarized by the IPCC AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced noise-induced tipping points such as Amazon forest dieback, in narrow regions of the parameter in response to specified values of CO₂ concentration or temperature increases. Noise-induced tipping events develop from fluctuations within the system.

Bifurcation tipping from one state to another can occur if a critical threshold is exceeded. The new state is defined as irreversible in this context if the recovery from the new state takes substantially longer than decades to centuries. In other words, tipping points are points of no return, at least on the century timescale. An example of bifurcation tipping would be the collapse of the West Antarctic ice sheet from marine ice sheet instability, or collapse of the Atlantic Meridional Overturning Circulation in response to North Atlantic changes such as freshwater input from rainfall and ice sheet melt.

The alarm surrounding climate tipping points is reflected by The Global Tipping Points Report that was launched at the COP28 on 6 December 2023 (Lenton et al., 2023) [HYPERLINK "https://report-2023.global-tipping-points.org"] It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate “tipping point” is a moving target. The most common examples of climate tipping points discussed in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason Most of these examples are noise-induced tipping events. There seems to be very little to discriminate between a noise-induced tipping event and natural climate variability. —a Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of the Greenland and West Antarctic ice sheets. These impacts can be reversed on the decadal timescales associated with natural climate variability and ecosystem responses

Bifurcation—Some tipping-point abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). The IPCC AR6 WG1 Summary for Policy Makers states:

"The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st

century for all emission scenarios. While there is high confidence in the 21st century decline, there is only low confidence in the magnitude of the trend. There is medium confidence that there will not be an abrupt collapse before 2100." (C.3.4)

"There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5)." (B.5.2)

For the purpose of SCC calculations the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future.

In summary, the term climate "tipping point" is overused to refer to changes arising from the slow creep of global warming in combination with natural climate variability. With regards to bifurcations which are more legitimately characterized as tipping points, "The IPCC AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz et al. incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107)

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In summary, there may be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been taken into account the result is only a modest increase in the SCC value—There is no actual large-scale bifurcation threshold in the climate that has been clearly linked to a specific amount of global warming. Further, there may be unknown bifurcation tipping points that are associated with natural climate processes. Hence, there is little rationale for explicit inclusion of tipping points in evaluations of the Social Cost of Carbon in the 21st century.

Dietz, S., J. Rising, T. Stoerk, G. Wagner (2021) Economic impact of tipping points in the climate system. PNAS 2021 Vol. 118 No. 34 e2103081118

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Dakos, Vasilis, Chris Boulton, Joshua Buxton et al. (2024) Tipping point detection and early warnings in climate, ecological, and human systems, *Earth System Dynamics* 15 1117–1135 [HYPERLINK "<https://doi.org/10.5194/esd-15-1117-2024>"]

Palmer, TN, A Döring and G Seregin (2014) The real butterfly effect, *Nonlinearity* 27(9) 10.1088/0951-7715/27/9/R123 [HYPERLINK "<https://iopscience.iop.org/article/10.1088/0951-7715/27/9/R123/meta>"]

2 Direct Impacts of CO₂ on the environment

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50% of the Earth versus “browning” over only 4%, and attributed 70% of the greening to rising CO₂ levels (see Figure 2.1).

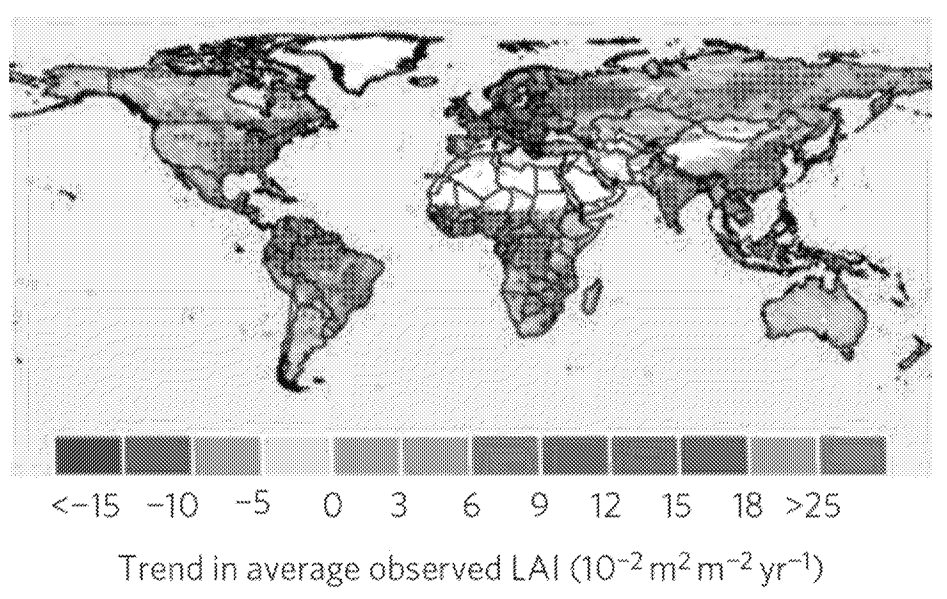


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were exploiting it through land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis in response to rising CO₂, Haverd et al. (2020) reported a CO₂ fertilization rate nearly double what models had predicted. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and climate policy will be discussed in Chapter 10.

Finally, Chen et al. surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55% of the globe while browning was accelerating over only 7%. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver

2.1.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth's atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2

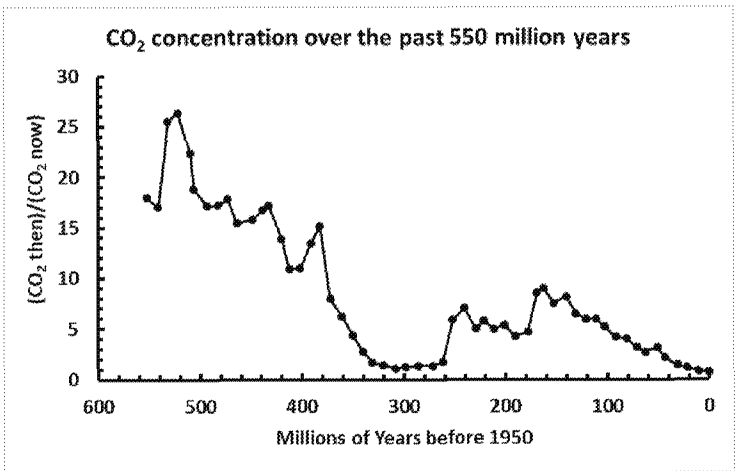


Figure 2.2. Ambient CO₂ levels over the past 550 million years as a multiple of current levels. Source: Adapted from Berner (2006). Current CO₂ levels correspond to about 1.3 times the indicated value at 0.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024).

Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010).

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

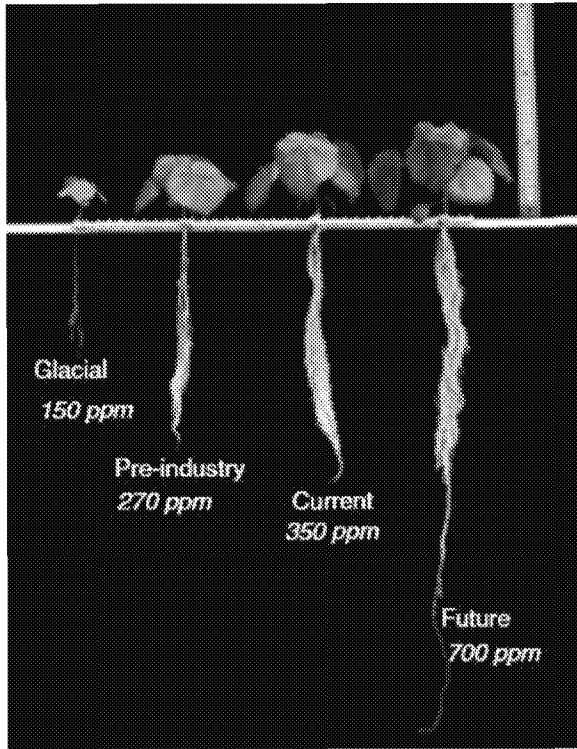


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

Specific effects of climate change on US agriculture will be reviewed in Chapter 10.

2.1.3 Rising CO₂ and crop water use efficiency

Derynget al. (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂ Enrichment—see Chapter 10) on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them so that all regions showed a net CWP gain. Derynget al (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90% for rice and 60% for maize.

Similarly, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Derynget al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.1.4 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions had been discovered to be causing global crop declines and regional browning, that surely would have been discussed prominently in IPCC reports, perhaps even with its own chapter in an Assessment Report if not an IPCC Special Report. By contrast the IPCC has been almost silent on the topic of global greening and CO₂ fertilization of agricultural crops.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report entitled “global greening and browning” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries and Synthesis Reports conspicuously fail to discuss the topic.

2.2 Ocean Alkalinity

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increase, more is absorbed

by the oceans, which decreases alkalinity. Depending upon the buffering capacity of the oceans, the oceans are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

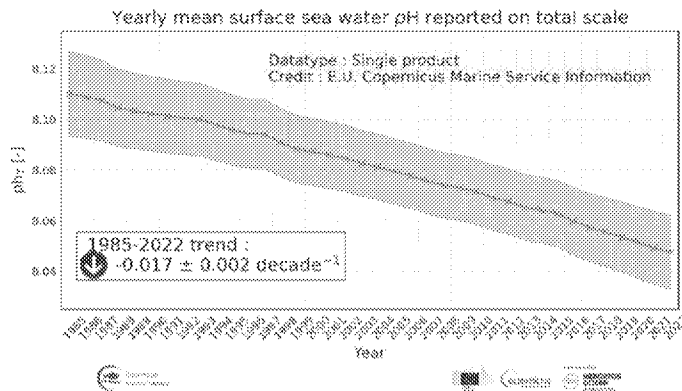


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5 - to 7.0 (Krissansen-Totton et al., 2018). On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De'ath et al. (2009) reported that a portion of Australia's Great Barrier Reef (GBR, the world's largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd et al. (2013) showed that report to have resulted from a biased data analysis which, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study compared to only 11 citations for the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates a strong rebound has occurred in coral production (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods

Commented [TF1]: As you did with CO2 in the ambient air, I might suggest noting that a pH of [insert range, probably 6.5 to 9] is perfectly harmless for human beings to swim in, drink (my sparkling water is apparently about a 5 on the pH scale), etc.

“Ocean acidification” is cleverly terrifying, and I think untrained readers would be interested to know that swimmable streams can have a pH below 7, for example, with no direct adverse impacts on humans. [HYPERLINK “https://www.epa.gov/caddis/ph” \h]

Commented [TF2]: Could we rephrase this to say “have been exposed to wide ranges in pH over time.”?

At minimum, I think we should delete the word “anyway” because it (rightly or wrongly) would be interpreted as dismissive.

I'll try to flag these heartburn words throughout my review.

Hole 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has come as a surprise to some observers.

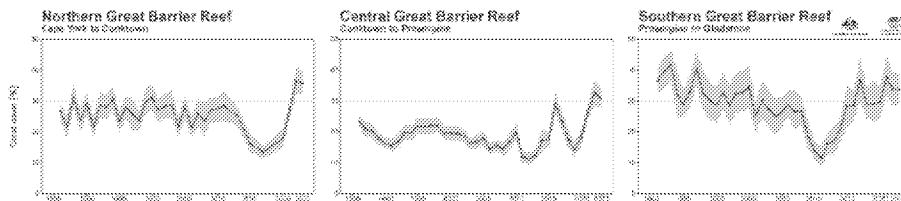


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

2.2.3 Publication bias

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the impacts of declining ocean pH. An *ICES Journal of Marine Science* Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016)

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.
Clements et al. (2022)

Commented [SK3]: Can/should we say anything about lab experiments that attempt to assess the effects of OA? [generally not valid, in my opinion]

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. Changes to the Australian Great Barrier Reef are driven by many factors other than temperatures or alkalinity and coral cover has recently staged a major rebound. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

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3. Increasing CO₂ and the Alkaline Oceans

[Ross May 12 edit notes: added citation for pH figure. Moved paleo paragraph closer to start. It was decided to reword various paragraphs to remove passive tense where possible. Expanded discussion of Clements et al – quite an important article – and updated the citation to the published version. Expanded the concluding paragraph]

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A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is basic and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025)⁴, down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011).⁴ As CO₂ concentrations in the atmosphere increase, more is absorbed by the oceans, which decreases alkalinity. Depending upon the alkalinity (buffering capacity) of the oceans, the oceans are expected to become somewhat less alkaline over time, putatively explaining consistent with the observed decrease in pH from 8.2 to 8.1 over the last few hundred years.

Commented [SK1]: Perhaps include an image like the following from [HYPERLINK "https://marine.copernicus.eu/access-data/ocean-monitoring-indicators/global-ocean-acidification-mean-sea-water-ph-time-series"]

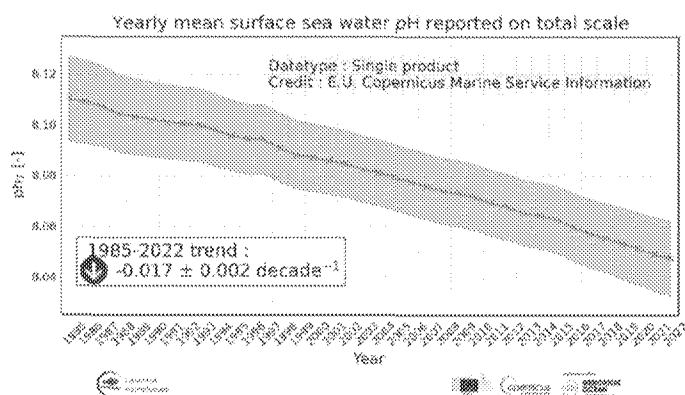


Figure 3.1: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

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While this process is often called “ocean acidification”, this is a misnomer because the oceans are not expected to become acidic (pH less than 7.0); “ocean neutralization” would be more accurate. And Even if the water were to turn acidic, that was to happen, it is believed that life in the oceans evolved during a period when the oceans were mildly acidic with, with a pH of 6.5 - to 7.0 (Kriessens-Totton et al., 2018).

⁴ A neutral aqueous solution has a pH of 7.0, while one with pH > 7.0 is basic and pH < 7 is acidic.

On the time scale of thousands of years, boron isotope proxy measurements of pH show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae et al., 2018). Thus, there appears to be considerable resilience of ocean biota to natural long-term changes in ocean pH since marine organisms are exposed to wide ranges in pH anyway.]

For many years it had long been assumed there are concerns that a decreasing pH of sea water would will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef, measured pH values. This results in pH values that have been measured to range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957).

De'ath et al. (2009) in 2009 it was reported that a portion of Australia's Great Barrier Reef (GBR, the world's largest coral reef ecosystem) had experienced a 14% decline in calcification since 1990 (De'ath et al., 2009). This was tentatively attributed to increasing water temperature and decreasing pH of seawater. But since that time, the initial 2009 Ridd et al. (2013) that report of reduced calcification rates in the GBR was reported was shown showed that report to have been the result of a biased in the data analysis (Ridd et al., 2013) which, when corrected, and correction for this bias led to showed no change in calculated calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) received by the original study as compared to only 11 citations for the subsequent study correction (as of 30 April 2025).

[The most recent annual summary of GBR conditions from the Australian Institute of Marine Science was titled, *Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef* indicates a strong rebound has occurred in coral production (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole 2023), and recovery of the reef from storm damage takes years. Given the reported declines in GBR coverage calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels, it the rebound has come as a surprise to some observers that the decline reversed over the last decade or so, with Woods Hole Oceanographic Institution asking, "Is the Great Barrier Reef Making a Comeback?" (Woods Hole, 2023). The most recent annual summary of GBR conditions from the Australian Institute of Marine Science was titled, *Continued Coral Recovery Leads to 36-year Highs across Two-Thirds of the Great Barrier Reef* (AIMS, 2022). Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden et al., 2015), and recovery of the reef from storm damage takes years.

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It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) leads to exaggerated impacts from more alkaline oceans exaggerates the impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, "As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish." (Browman, 2016)

Commented [TF2]: Could we rephrase this to say "have been exposed to wide ranges in pH over time."?

At minimum, I think we should delete the word "anyway" because it (rightly or wrongly) would be interpreted as dismissive.

I'll try to flag these heartburn words throughout my review.

Commented [RM3]: I moved this para closer to the start

Commented [TF4]: As you did with CO₂ in the ambient air, I might suggest noting that a pH of [insert range, probably 6.5 to 9] is perfectly harmless for human beings to swim in, drink (my sparkling water is apparently about a 5 on the pH scale), etc.

"Ocean acidification" is cleverly terrifying, and I think untrained readers would be interested to know that swimmable streams can have a pH below 7, for example, with no direct adverse impacts on humans. [HYPERLINK "<https://www.epa.gov/caddis/ph>"]

Commented [TF5]: Would you all be comfortable using a graph to show the rebound? This article features a set of three graphs (looks like from an underlying study) for different regions of the GBR that I think could help readers visualize this point: [HYPERLINK "<https://theconversation.com/is-the-great-barrier-reef-reviving-or-dying-heres-whats-happening-beyond-the-headlines-210558>"]

Commented [RM6]: My read of that article is not so much surprise at the recovery as an attempt to reassure the public that it won't last.

Similarly, a meta-analysis (Clements et al., 2021) of the negative effects of ocean acidification on reef fish behaviors found what they called a “decline effect”: that initially dramatic conclusions published in the scientific literature prominent journals showing apparently large reported effects of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects were all but refuted upon subsequent analysis involving larger sample sizes of data (Clements et al., 2021). They call for their colleagues to improve research practices to prevent the “decline effect” from persisting:

Commented [SK7]: Can/should we say anything about lab experiments that attempt to assess the effects of OA? (generally not valid, in my opinion)

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research.

Clements et al. (2022)

In conclusion, it is becoming increasingly apparent that much of the public discussion of the effects of ocean “acidification” on marine biota has likely been exaggerated one-sided and exaggerated. Ocean life is complex and much of it evolved when the oceans were acidic relative to the present. There is a tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, whereas the subsequent research rebutting those findings tends to receive little attention.

Commented [SK8]: “likely” is pretty weak and incommensurate with the entire text above

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Dedining planetary albedo and recent record warmth

Planetary albedo is the fraction of incoming solar radiation that is reflected back into space by the reflective surfaces like cloud tops and snow on Earth's surface and atmosphere, rather than being absorbed at the surface. Earth's planetary albedo is approximately 30%, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed at the surface to be then re-radiated as heat into the atmosphere. Hence, other things being equal, a decline in Earth's albedo is associated with a warming of the atmosphere.

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Arguably the most striking change to the Earth's climate system in the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure xxx shows the planetary albedo variations since 2000, when we have good satellite observations. The 0.5% reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in ~~in~~ solar energy averaged over the planet (Hansen and Karecha, 2025). For reference, doubling of CO₂ has a direct radiative impact of about 1.2 W/m².

Looking back prior to 2000 with less adequate data, Gossling et al. (2025) assessed that planetary albedo was relatively low around the 1940's and 50's, before industrial aerosol precursor emissions led to global dimming until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum may have been the lowest since at least 1940.

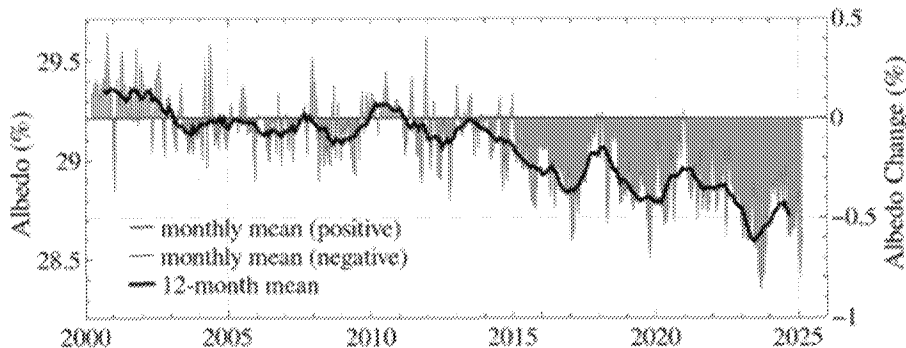


Figure xxx. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface characteristics can't explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5% since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England et al, 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that "There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability." (SPM, A.1.5)
- Northern hemispheric snowcover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer.

[[HYPERLINK "http://climate.rutgers.edu/snowcover/"](http://climate.rutgers.edu/snowcover/)]

- Global greening (Chapter 2) is contributing the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo increase associated with increasing forested area.

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as being caused by changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g. dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. In terms of pollution aerosol, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog et al., 2024; Yuan et al., 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al. 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the northern hemisphere, whereas in the southern hemisphere the decrease in planetary albedo is primarily from decreases in mid-level clouds across all latitude zones. Gosling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Niño event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic, reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al. 2021).

- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Niño Southern Oscillation (ENSO), which have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gossling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarez et al. 2025; Kuchar et al., 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes ~~from direct~~ by couplings between the stratosphere and troposphere. These papers indicate the complex interactions ~~and~~ between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

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identify a decadal mode of atmosphere–ocean variability in the North Atlantic with a dominant time scale of 13–18 years. Large-scale atmospheric circulation anomalies drive SST anomalies both through contemporaneous air–sea heat fluxes and through delayed ocean circulation changes, the latter involving both the meridional overturning circulation and the horizontal gyre circulation.

Declining planetary albedo and recent record warmth

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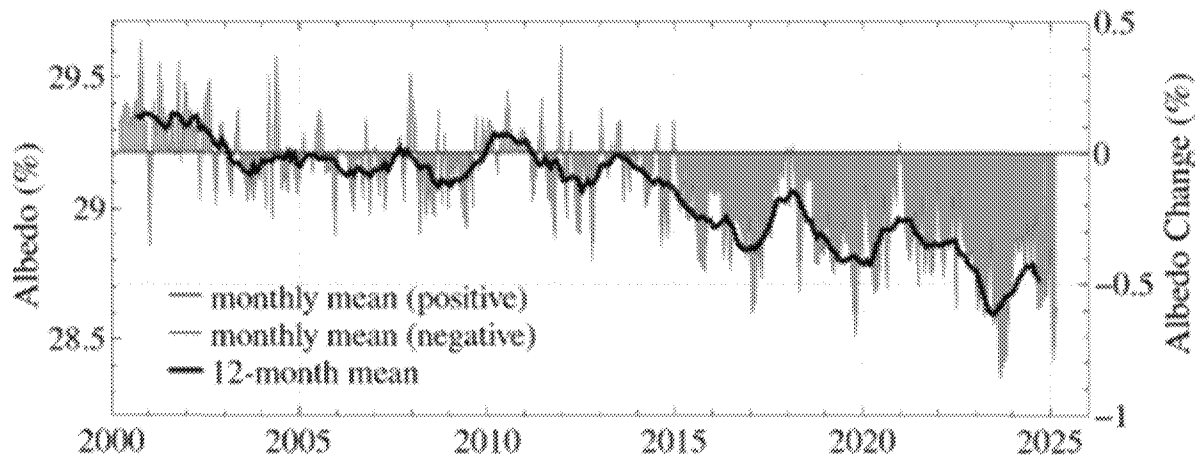


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Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as being caused by changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g. dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. In terms of pollution aerosol, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog et al., 2024; Yuan et al, 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the northern hemisphere, whereas in the southern hemisphere the decrease in planetary albedo is primarily from decreases in mid-level clouds across all latitude zones. Gosling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Niño event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic, reflecting a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al 2021).
- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Niño Southern Oscillation (ENSO), which have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gossling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz et al, 2025; Kuchar et al, 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes ~~from driven by~~ couplings between the stratosphere and troposphere. These papers indicate the complex interactions ~~and~~ between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

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identify a decadal mode of atmosphere–ocean variability in the North Atlantic with a dominant time scale of 13–18 years. Large-scale atmospheric circulation anomalies drive SST anomalies both through contemporaneous air–sea heat fluxes and through delayed ocean circulation changes, the latter involving both the meridional overturning circulation and the horizontal gyre circulation.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models show too little power relative to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov et al. 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

“Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence).” (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.]

Commented [SK1]: Shouldn't we say something about the early 20th century warming?

The time series of global surface temperature anomalies since 1850 shows irregular variations of significant amplitude against the background of an overall warming trend. The period between 1905-1945 shows a strong trend of warming. The following thirty years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

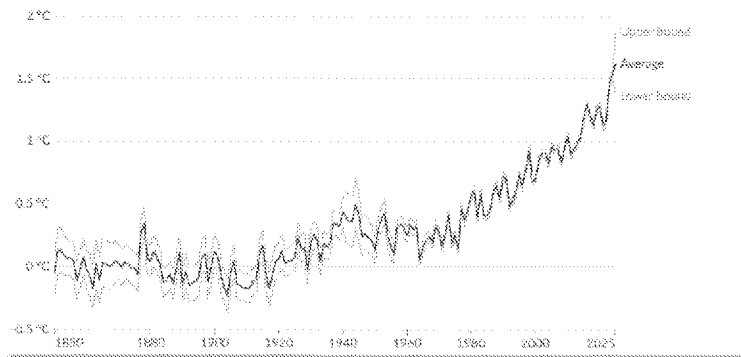


Figure 8.1 Global average surface temperature.

The causes of the early 20th century warming is discussed by Hegerl et al. (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941; hence this implies that the early increase in CO₂ had a small impact on the warming. Volcanic activity during this period was very low, and solar forcing is uncertain. Hegerl et al (2017) somehow inferred that 40-54% of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman et al (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular Mode was positive, with a strengthened Amundsen-Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid century was particularly pronounced in the Arctic. Bokunhava and Semenov (2021) find that most likely these variations were caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural [[HYPERLINK "https://www.sciencedirect.com/topics/earth-and-planetary-sciences/radiative-forcing"](https://www.sciencedirect.com/topics/earth-and-planetary-sciences/radiative-forcing) \o "Learn more about radiative forcing from ScienceDirect's AI-generated Topic Pages"] related to the reduced volcanic activity and variations of solar activity as well as growing greenhouse gases concentrations. Tokinaga et al (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale over the Northern Hemisphere. These same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes for the cooling have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation; cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson et al. (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947-1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

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6 Models versus Observations in the Recent Past

6.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide ~~the theoretical~~ evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. ~~In order to determine~~ ~~assess the value~~ ~~fitness~~ of climate models for this purpose, it is reasonable to ask how well they ~~have reproduced the current climate and its variations over the recent past century,~~ ~~say the last half-century.~~ The nearby box "Climate modeling" gives some detail on how climate models work.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three, ~~as we discussed in the previous chapter.~~ This range of disagreement among models has not changed for decades.

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Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

Box: Climate modeling

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All but the simplest computer models of the climate begin by covering the earth's land surface with a grid of squares, typically 100 km on a side. To describe the atmosphere, 10-20 layers of grid boxes are stacked above those squares. With a similar, but finer, grid covering the ocean, the model comprises one million grid boxes for the atmosphere and 100 million grid boxes for the ocean.

The computer models use the fundamental laws of physics to calculate how the air, water, and energy in each box at a given time move to neighboring grid boxes at a slightly later time; this time step can be as small as 10 minutes. Repeating this process millions of times simulates the climate for centuries, a calculation that can take months of computer time on even the most powerful supercomputers. Comparing the results of computer runs with what we know about past climates gives some sense of how good a model is. Calculations into the future under assumed human and natural influences then purport to describe the climate decades hence.

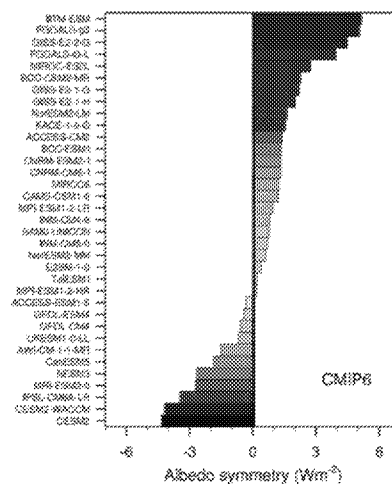
Unfortunately, while all this might sound straightforward, it isn't. A major problem is that many important phenomena are much smaller than the 100 km grid size. For example, flows of sunlight and heat through the atmosphere are influenced by clouds. Because there are far too many clouds to follow each in detail, researchers must make "subgrid" assumptions about the number and type of clouds in each grid box to build a complete model. Cloud cover is only one among dozens of subgrid assumptions. Another is *How much snow or ice is on the surface?* which controls the heating effect of sunlight.

Each subgrid assumption has numerical parameters that must be set, somehow. Modelers determine subgrid parameters based on what they know about physics and weather and climate observations.

and then run the model. Since the results generally don't much look like the climate system we observe, modelers adjust ("tune") these parameters to better match some features of the real climate system. Different modelers will make different assumptions with different tunings and so produce widely different results.

Tuning is a necessary, but perilous, part of modeling the climate, as it is in modeling of any complex system. An ill-tuned model will be a poor description of the real world, while overtuning risks cooling the books—that is, predetermining the answer, for example, a [HYPERLINK "https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018MS001400"]...laying out the details one of the most esteemed models, that of Germany's Max Planck Institute, tells of tuning a subgrid parameter (related to convection in the atmosphere) by a factor of ten because the value chosen originally resulted in twice as much warming as had been observed.

To extract useful information from vastly different models, results are usually quoted as averages over a collection ("ensemble") of models; the most recent UN IPCC assessments used the CMIP6 ensemble. The diversity of that ensemble is already evident in one of the simplest descriptions of the climate – the earth's average surface temperature. It varies across the ensemble by about 3°C, three times greater than the observed warming during the 20th century. And the models differ just as significantly when you start to look at the details of their results. For example, since you're not allowed to tune the freezing temperature of water (as it's determined by Nature), the amounts of snow and ice cover might be very different for models with different surface temperatures. That can be seen in the [HYPERLINK "<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2022GL101802>"] below, which shows the differences between the sunlight absorbed by the Northern and Southern hemispheres for the CMIP6 models. It is disturbing that the range is large compared both to the observed value and to current human influences (about 2.5 Wm⁻²).



Caption: Differences in the reflectivity (albedo) between the Northern and Southern Hemispheres for members of the model ensemble used in the most recent IPCC assessment. The very small observed difference is indicated by the vertical black line.

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While it would be reassuring if the models were able to accurately describe the current climate, the crucial issue for society is how well they describe the response of the climate to physically small human influences such as warming greenhouse gases, cooling aerosols, and changes in land use. Here, the most important thing that a model has to get right are “feedbacks.” Here’s how feedbacks work. The growing greenhouse gas concentrations that raise the global temperature can also cause other changes in the climate system that either amplify or suppress their direct warming influence. For example, as the globe gets warmer, there’ll be less snow and ice on the surface, which decreases the planet’s reflectivity. The less reflective earth will then absorb more sunlight, causing even more warming. Other important feedbacks involve the amount of water vapor and clouds in the atmosphere or the temperature profile of the atmosphere. The average of results over the many different models in the ensembles suggests that the net effect of all feedbacks is to double or triple CO₂’s direct warming influence.

End BOX

6.2 Surface warming

A straightforward test of a climate model’s validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 6.1 is reproduced from Scaffeta (2023), a peer-reviewed 2023 study which ~~that~~ groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

~~Columns correspond to model groups showing low-ECS to high-ECS. Rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.~~

~~Examination of~~ The leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

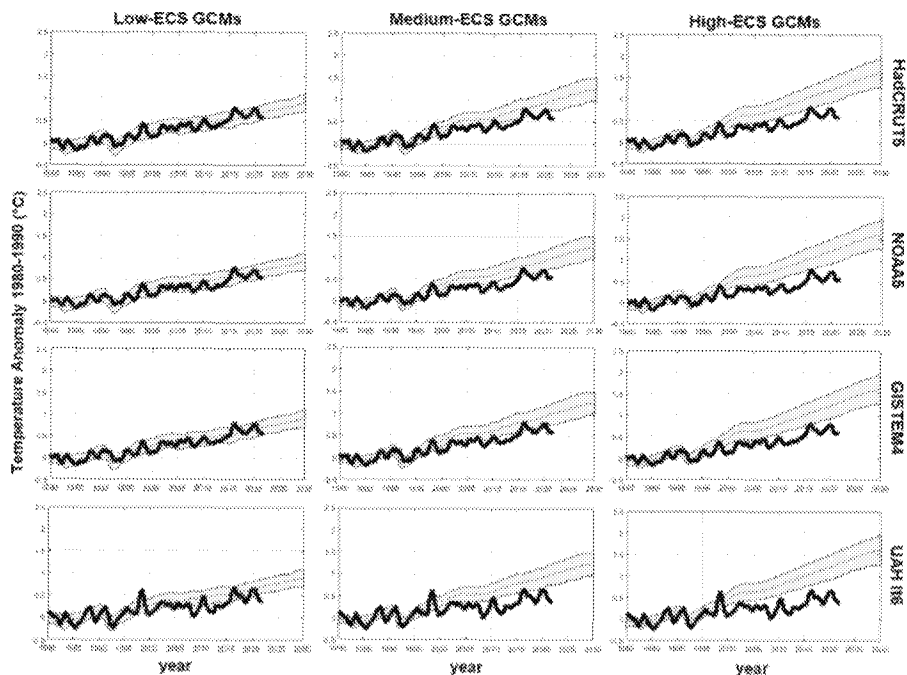


Figure 6.1: model-observational comparisons for Earth's surface warming. The columns correspond to model groups showing low-ECS to high-ECS, while the rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source.

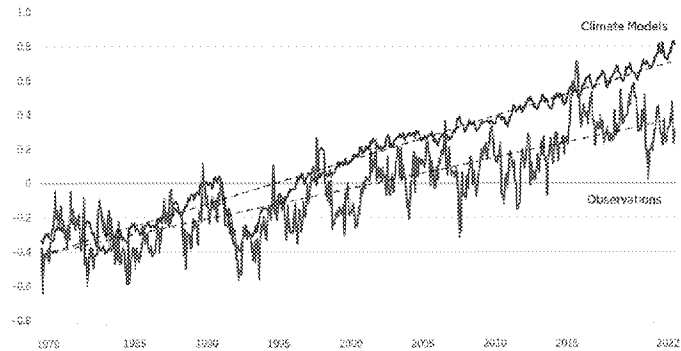
Source: Scafetta N. Climate Dynamics 2023 Fig2. Rows: temperature data products as indicated. Columns: Low- to High- ECS models. Observations: black line. Model simulations: yellow band.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by focusing comparing on-average surface temperature data products with versus the average climate model warming, as summarized in Figure 6.2.

Figure 6.2

Global Average Surface-Air Temperature Variations, 1979–2022

DEPARTURE FROM 1951–1980 AVERAGE, IN DEGREES CELSIUS



NOTE: Figures have been adjusted to align trends starting in 1979.

SOURCES: Author's calculations based on data from five different observation-based datasets and 26 climate models taking part in the sixth IPCC Climate Model Intercomparison Project, and NOAA Climate Explorer, "Starting Points," <https://climate.noaa.gov/starting-points> (accessed January 30, 2024).

Figure 6.2: Models versus observations at the surface. Source: Spencer (2024)

6.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the tropical troposphere. Since this region generates the bulk of atmospheric warming in a GCM model, it is important to get the trends right. The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time, ~~not better~~, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming rates in CMIP6 climate models to observations from satellites, weather balloons and reanalysis systems (Figure 6.3). Every ~~single~~ model overpredicts the observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics (Figure 6.4).

In most individual cases the bias is statistically significant and on average it is highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. ~~If a group of future models were to appear that had a realistically representation of global tropospheric warming, they would likely have to have a lower ECS be less sensitive~~ than even the low-ECS members of the CMIP6 ensemble

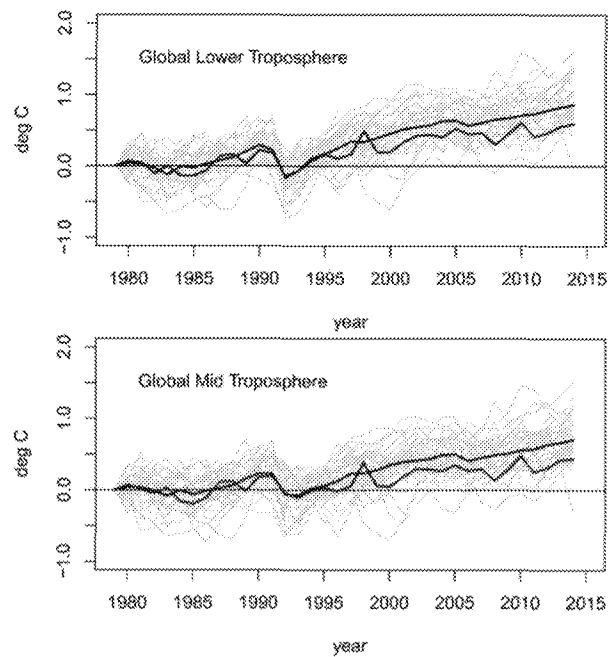


Figure 6.3: Models versus observations in the global troposphere. Source: McKittrick and Christy (2020). Gray lines: individual model runs. Black: average model run. Blue: average of satellite, radiosonde and reanalysis observations.

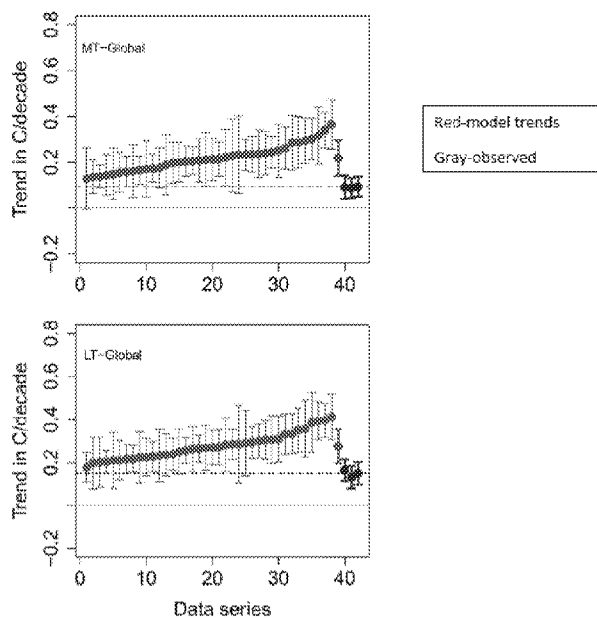


Figure 6.4: Modeled versus observed warming trends in the global troposphere. Adapted from McKittrick and Christy (2020). Red dots: model warming trend in $^{\circ}\text{C}/\text{decade}$ with 95% confidence interval bars. Gray dots: observed warming trends in 3 data products (satellite, radiosondes and reanalysis) and 95% confidence interval bars.

Spencer (2024) shows the mismatch is also present in the lower troposphere:

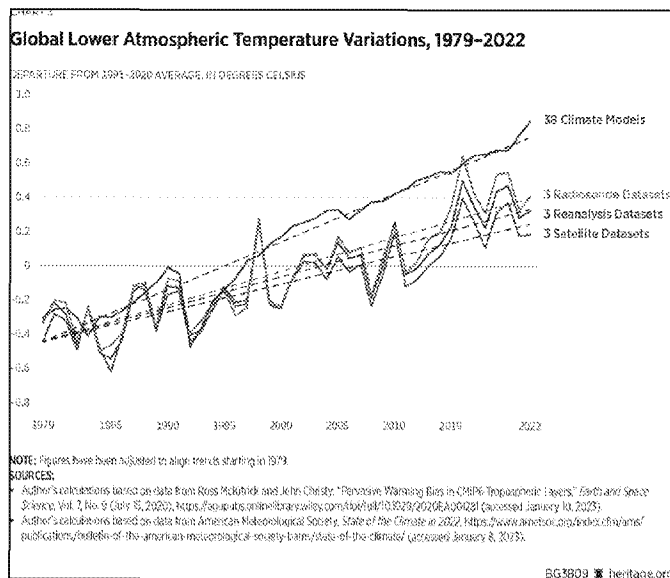


Figure 6.5: Comparison of average trends in lower troposphere, 1979–2022. Source: Spencer (2024).

As mentioned the IPCC has long acknowledged the model-observational mismatch. For example, The AR6 pp. 443–444 offers this on the tropical confinement model-observational mismatch in the troposphere the tropics (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). ... Hence, we assess with *medium confidence* that CMIP5

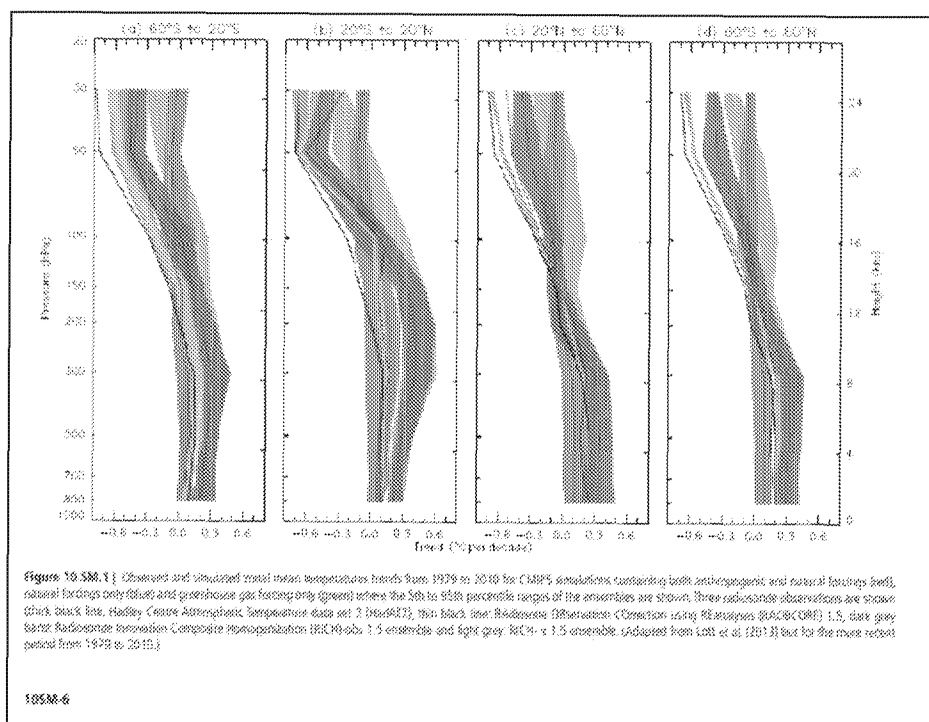
and CMIP6 models continue to overestimate observed warming in the upper troposphere over the 1979–2014 period by at least 0.1°C per decade,

Notably, it is worth noting that despite the enormous accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias. In other contexts they declare *high confidence* in phenomena established with much less evidence.

6.4 Vertical profile mismatch and excess amplification

Another important model-observational discrepancy is the excess amplification with altitude found in climate models. A comparison was shown in the IPCC AR5 Chapter 10, although only in the online supplement. The diagram, reproduced below as Figure 6.6, compares temperature trends by altitude between models and observations, divided up into four separate latitude bands.

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Figure 6.6: Vertical warming pattern by latitude band. Source: IPCC AR5 Figure 10.SM.1

The Figure is not referenced in the main report nor in any summary. What it shows, although it is not apparent at first glance, is it shows that the 1979-2010 warming in the lower troposphere is so minimal small as to be it is consistent with models having no GHG forcing in them at all, and is

inconsistent with the model runs that do have GHG forcing. Here is the main global band (60S to 60N) expanded with the observed trends highlighted in yellow:

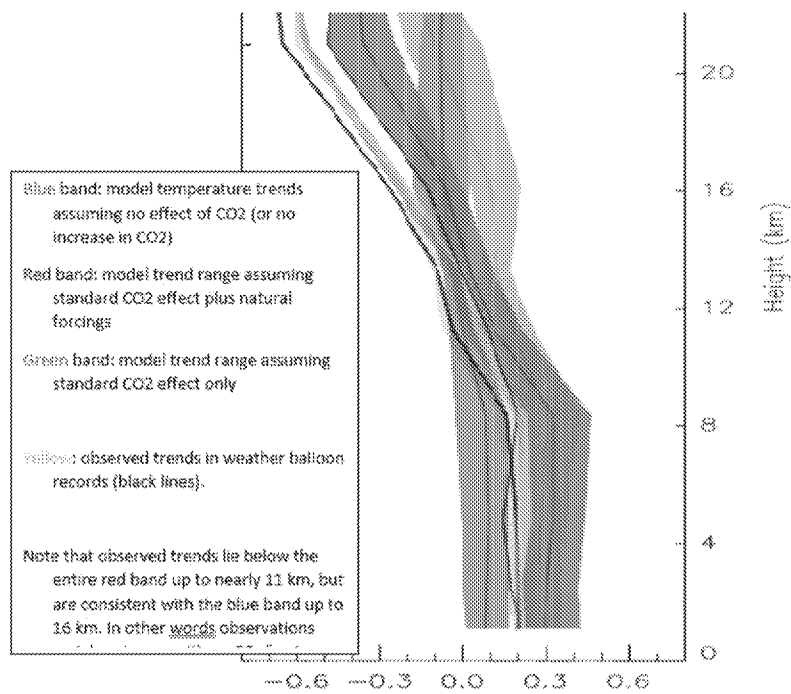


Figure 6.7: Adapted from IPCC AR5 Figure 10.SM.1

The next version of the Figure draws further detail out of the tropics band:

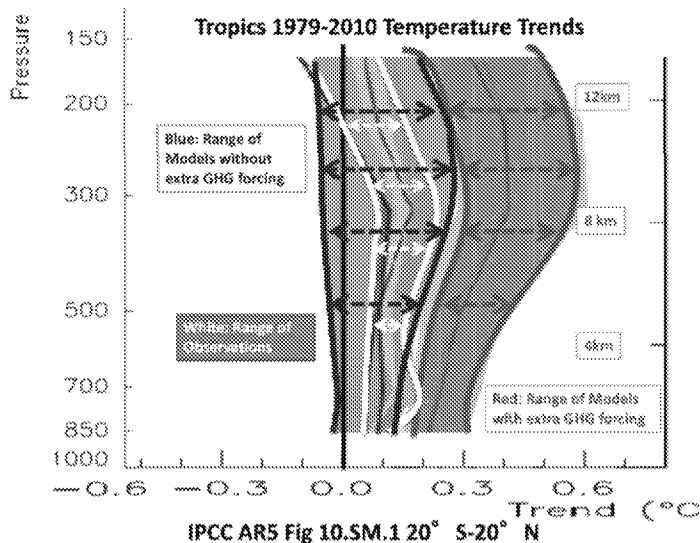


Figure 6.8: Adapted from IPCC AR5 Figure 10.SM.1.

In the tropics, where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 6.9. Modeled temperature trends exceed balloon observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 6.9 is the TTT layer average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

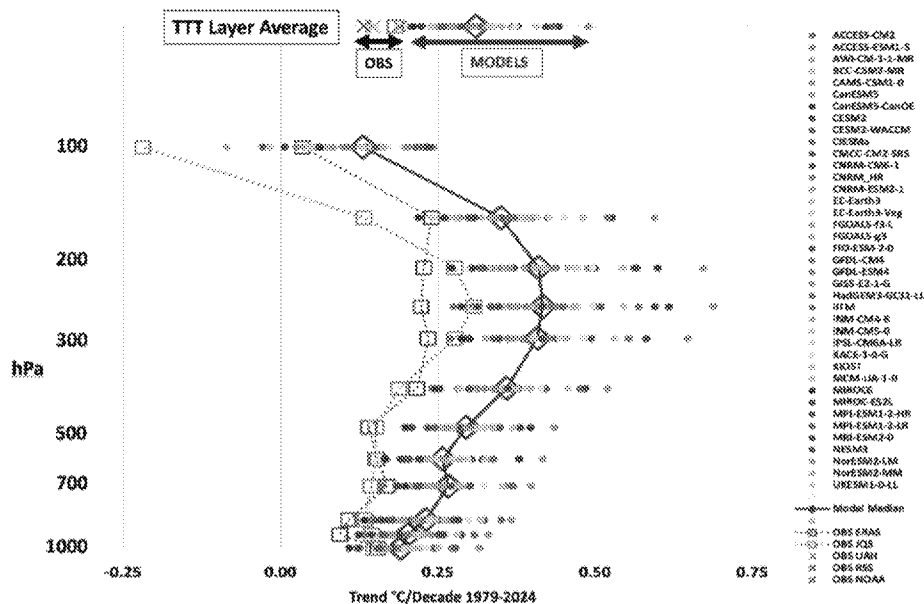


Figure 6.9: Modeled versus observed warming, tropical troposphere. Source: Christy and McNider (2017).

Some defenders of the models have argued that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), which was not discussed in the AR6, showed that models project greater amplification with altitude than is observed. That paper gave rise to an online debate over whether the amplification rates were being correctly calculated, and whether the discrepancy between models and observations was statistically significant. The topic involves very advanced statistical theory and was dealt with by two experts in time series analysis (Vogelsang and Nawaz 2016) who found that Klotzbach’s conclusions were valid, and that observed amplification is significantly smaller than the model-projected rates. The IPCC AR6 made no mention of this work either.

6.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to the year 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with **the bulk of the decrease prior to 2000**. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

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It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate **models project continued tropospheric warming and stratospheric cooling over the coming decades**. Global average satellite observations of **lower stratospheric temperatures exhibit no significant trends since the turn of the century**. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated **radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.**”

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6.6 Water vapour trends mismatch

Much of the warming in climate models derives not from GHG increases themselves but from water vapour feedbacks: extra warming induced by the projected accumulation of water vapour in the atmosphere after it warms due to CO₂. But new evidence (Simpson et al. 2024) shows that models have over-projected increases in humidity.

“Water vapor in the atmosphere is expected to rise with warming because a warmer atmosphere can hold more moisture. However, over the last four decades, **near-surface water vapor has not increased over arid and semi-arid regions**. This is **contrary to all climate model simulations** in which it rises at a rate close to theoretical expectations, even over dry regions. This may indicate a major model misrepresentation of hydroclimate-related processes; **models increase water vapor to satisfy the increased atmospheric demand, while this has not happened in reality.**”
(Simpson et al. 2024)

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While the models and observations matched over the 1988 to 2006 interval they diverge after that, directly contradicting model projections.

6.7 Snow cover mismatch

According to the Data compiled by the Rutgers University Snow Lab (undated) show that the Northern Hemisphere winter snow cover is not decreasing. If anything, shows an increasing trend over time.

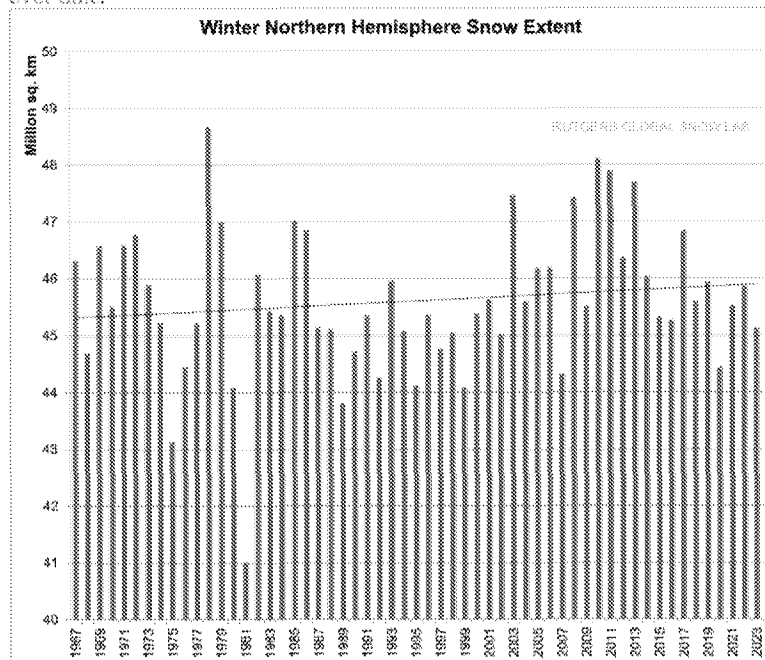


Figure 6.10: Northern Hemisphere Winter Snow extent. Source: [[HYPERLINK "https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1"](https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1)] (February 24, 2024)

Yet models project declining Northern Hemisphere snow cover due to climate warming, as described. But observations do not support this, as explained by Connolly et al. (2019).

Observed changes in Northern Hemisphere snow cover from satellite records were compared to those predicted by all available Coupled Model Intercomparison Project Phase 5 ("CMIP5") climate models over the duration of the satellite's records, i.e., 1967–2018. A total of 196 climate model runs were analyzed (taken from 24 climate models). Separate analyses were conducted for the annual averages and for each of the seasons (winter, spring, summer, and autumn/fall). A longer record (1922–2018) for the spring season which combines ground-based measurements with satellite measurements was also compared to the model output. The climate models were found to poorly explain the observed trends [in Northern Hemisphere snow cover]. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions. Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant. Connolly et al. (2019); emphasis added.

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6.8 US Corn Belt

One of the largest discrepancies between models and observations can be found when we test them in the U.S. Corn Belt, in a region of particular importance to global food production, the U.S. Corn Belt. Figure 6.11 shows the warming trends for summertime (June, July, August) for the U.S. 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) produced too much warming, warm far too rapidly compared to observations (blue), during 1973 to 2022.

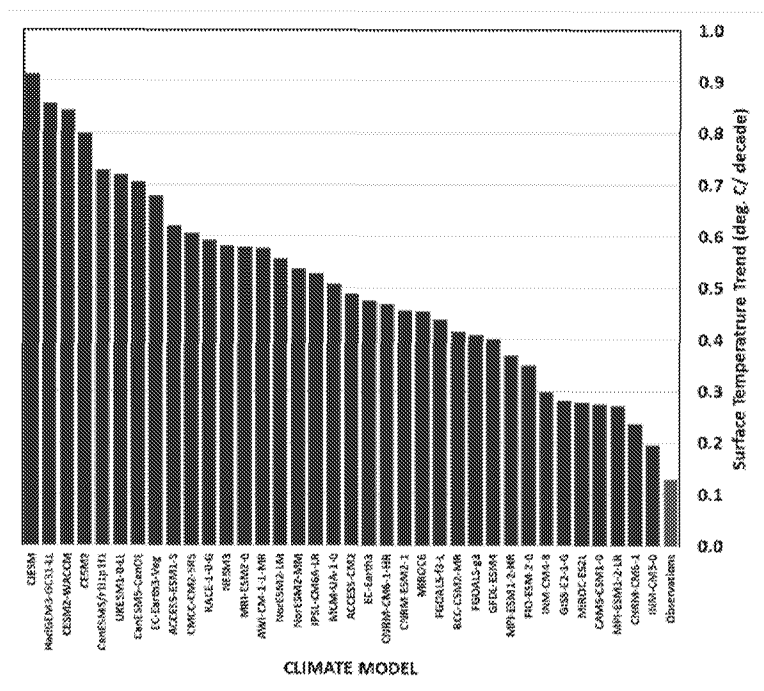


Figure 6.11: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 10, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, which is in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower- and mid-troposphere and too much amplification of warming aloft

- They also produce too much stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt.
- The IPCC has acknowledged some of these issues, buried the amplification problem and ignored others.
- * The warm bias discussed here is consistent with independent evidence of model bias presented in Chapters 5 (measuring climate sensitivity) and 9 (optimal fingerprinting). Given the persistent warm bias in so many key aspects of climate model performance, users are justified in assuming that projections of future warming are also very likely to be biased too warm.

As has been noted by two leaders of the modeling community,

...for many key applications that require regional climate model output or for assessing large-scale changes from small-scale processes, we believe that the current generation of models is not fit for purpose. - [HYPERLINK "https://www.pnas.org/content/116/49/24390"]

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LT Global

	RAOBCOR	RICH17	RATPAC	UAHv6.0	RSSv4.0	NOAA	Avg Sat	ERA5
1958	-0.444	-0.528	-0.513					-0.395
1959	-0.463	-0.562	-0.601					-0.454
1960	-0.508	-0.612	-0.619					-0.571
1961	-0.455	-0.578	-0.568					-0.523
1962	-0.614	-0.727	-0.706					-0.613
1963	-0.583	-0.687	-0.689					-0.582
1964	-0.710	-0.810	-0.933					-0.755
1965	-0.804	-0.907	-0.947					-0.805
1966	-0.640	-0.736	-0.721					-0.560
1967	-0.622	-0.706	-0.725					-0.661
1968	-0.766	-0.859	-0.797					-0.724
1969	-0.521	-0.619	-0.582					-0.452
1970	-0.489	-0.545	-0.577					-0.507
1971	-0.811	-0.865	-0.862					-0.801
1972	-0.625	-0.689	-0.685					-0.616
1973	-0.328	-0.398	-0.426					-0.373
1974	-0.720	-0.767	-0.783					-0.783
1975	-0.692	-0.743	-0.739					-0.730
1976	-0.860	-0.931	-0.922					-0.860
1977	-0.433	-0.527	-0.451					-0.427
1978	-0.440	-0.532	-0.545					-0.490
1979	-0.360	-0.442	-0.414	-0.346	-0.495		-0.421	-0.303
1980	-0.213	-0.287	-0.275	-0.178	-0.344		-0.261	-0.235
1981	-0.240	-0.306	-0.282	-0.248	-0.358	-0.272	-0.293	-0.261
1982	-0.466	-0.530	-0.518	-0.433	-0.560	-0.393	-0.462	-0.466
1983	-0.267	-0.321	-0.362	-0.178	-0.327	-0.131	-0.212	-0.235
1984	-0.533	-0.586	-0.567	-0.374	-0.590	-0.402	-0.455	-0.504
1985	-0.493	-0.553	-0.530	-0.498	-0.645	-0.438	-0.527	-0.535
1986	-0.403	-0.481	-0.487	-0.356	-0.528	-0.274	-0.386	-0.413

1987	-0.125	-0.201	-0.242	-0.087	-0.233	0.033	-0.096	-0.135
1988	-0.112	-0.160	-0.196	-0.098	-0.264	0.012	-0.117	-0.090
1989	-0.373	-0.409	-0.446	-0.346	-0.467	-0.234	-0.349	-0.318
1990	-0.085	-0.113	-0.210	-0.124	-0.290	-0.015	-0.143	-0.065
1991	-0.083	-0.112	-0.245	-0.116	-0.245	0.006	-0.118	-0.090
1992	-0.414	-0.447	-0.512	-0.417	-0.518	-0.289	-0.408	-0.376
1993	-0.330	-0.366	-0.446	-0.339	-0.453	-0.275	-0.356	-0.346
1994	-0.266	-0.297	-0.293	-0.201	-0.318	-0.152	-0.224	-0.255
1995	-0.201	-0.227	-0.190	-0.067	-0.177	-0.053	-0.099	-0.141
1996	-0.324	-0.343	-0.369	-0.146	-0.278	-0.156	-0.193	-0.246
1997	-0.298	-0.316	-0.324	-0.144	-0.242	-0.159	-0.182	-0.245
1998	0.232	0.220	0.155	0.347	0.224	0.306	0.292	0.220
1999	-0.253	-0.259	-0.303	-0.153	-0.243	-0.211	-0.202	-0.280
2000	-0.284	-0.291	-0.326	-0.157	-0.248	-0.221	-0.208	-0.315
2001	-0.119	-0.137	-0.132	-0.022	-0.079	-0.061	-0.054	-0.130
2002	0.016	-0.006	-0.031	0.080	0.033	0.035	0.049	-0.001
2003	0.009	-0.008	0.024	0.050	0.048	0.014	0.037	-0.012
2004	-0.088	-0.091	-0.081	-0.056	-0.024	-0.088	-0.056	-0.104
2005	0.093	0.106	0.141	0.063	0.110	0.040	0.071	0.044
2006	-0.017	0.000	0.065	-0.023	0.020	-0.044	-0.016	-0.035
2007	0.042	0.059	0.050	0.023	0.055	0.000	0.026	0.015
2008	-0.254	-0.239	-0.199	-0.238	-0.153	-0.250	-0.214	-0.240
2009	-0.012	-0.001	0.013	-0.043	0.009	-0.043	-0.025	-0.027
2010	0.140	0.151	0.233	0.194	0.254	0.197	0.215	0.250
2011	-0.130	-0.115	-0.034	-0.120	-0.072	-0.109	-0.100	-0.075
2012	-0.059	-0.044	0.022	-0.084	-0.006	-0.084	-0.058	-0.035
2013	0.073	0.091	0.136	-0.001	0.069	0.004	0.024	0.068
2014	0.117	0.138	0.167	0.044	0.127	0.056	0.075	0.113
2015	0.270	0.287	0.302	0.137	0.260	0.154	0.183	0.221
2016	0.595	0.610	0.554	0.388	0.456	0.389	0.411	0.499
2017	0.355	0.373	0.382	0.265	0.332	0.240	0.279	0.359
2018	0.249	0.268	0.264	0.088	0.193	0.101	0.127	0.233
2019	0.470	0.492	0.481	0.296	0.401	0.293	0.330	0.437
2020	0.475	0.505	0.495	0.351	0.465	0.361	0.392	0.495
2021	0.238	0.275	0.298	0.138	0.271	0.184	0.197	0.290
2022	0.267	0.228	0.320	0.15	0.254	0.192	0.199	0.300
2023	0.515	0.530	0.573	0.432	0.551	0.475	0.486	0.585
2024	0.860	0.875	0.924	0.774	0.860	0.784	0.806	0.914
2025								
79-24	0.195	0.217	0.232	0.152	0.228	0.146	0.176	0.195
95-19	0.243	0.263	0.277	0.108	0.210	0.126	0.148	0.225

0.444
0.405
0.340
0.374
0.196
0.207
0.060
-0.053
0.091
0.089
-0.074
0.152
0.164

-0.178		
-0.011		
0.267		
-0.145		
-0.137		
-0.323		
0.083		
0.057		
0.117	0.102	0.160
0.245	0.235	0.276
0.199	0.194	0.246
-0.047	-0.051	-0.014
0.132	0.136	0.119
-0.153	-0.151	-0.108
-0.132	-0.140	-0.095
-0.062	-0.089	-0.075
0.196	0.168	0.147
0.190	0.188	0.170
-0.091	-0.083	-0.103
0.178	0.191	0.109
0.160	0.171	0.051
-0.190	-0.186	-0.239
-0.126	-0.127	-0.196
-0.081	-0.079	-0.066
-0.035	-0.031	0.014
-0.179	-0.169	-0.188
-0.172	-0.164	-0.167
0.338	0.350	0.289
-0.166	-0.150	-0.192
-0.217	-0.204	-0.238
-0.071	-0.072	-0.068
0.044	0.038	0.011
0.018	0.014	0.042
-0.099	-0.091	-0.086
0.063	0.084	0.113
-0.066	-0.043	0.014
-0.027	-0.006	-0.024
-0.342	-0.326	-0.296
-0.120	-0.110	-0.107
0.012	0.020	0.090
-0.277	-0.267	-0.201
-0.226	-0.218	-0.168
-0.113	-0.105	-0.077
-0.089	-0.080	-0.069
0.045	0.047	0.043
0.351	0.350	0.271

0.091	0.090	0.077
-0.035	-0.036	-0.065
0.167	0.166	0.129
0.152	0.157	0.119
-0.104	-0.095	-0.101
-0.094	-0.163	-0.102
0.154	0.138	0.151
0.498	0.484	0.503

					LT Tropics		
JRA3Q	MERRA	Sonde Ave	Sat Avg	Reanal Avg	RAOBCOR RICH		
-0.568		-0.495		-0.482	1958	-0.215	-0.368
-0.658		-0.542		-0.556	1959	-0.436	-0.556
-0.730		-0.580		-0.651	1960	-0.398	-0.558
-0.711		-0.533		-0.617	1961	-0.605	-0.810
-0.788		-0.682		-0.700	1962	-0.610	-0.808
-0.738		-0.653		-0.660	1963	-0.500	-0.683
-0.837		-0.818		-0.796	1964	-0.623	-0.809
-0.909		-0.886		-0.857	1965	-0.747	-0.933
-0.710		-0.699		-0.635	1966	-0.430	-0.611
-0.795		-0.685		-0.728	1967	-0.662	-0.818
-0.865		-0.807		-0.794	1968	-0.671	-0.858
-0.580		-0.574		-0.516	1969	-0.159	-0.339
-0.685		-0.537		-0.596	1970	-0.193	-0.230
-0.939		-0.846		-0.870	1971	-1.076	-1.103
-0.751		-0.667		-0.684	1972	-0.469	-0.537
-0.552		-0.384		-0.462	1973	-0.303	-0.397
-0.923		-0.757		-0.853	1974	-0.902	-0.978
-0.870		-0.725		-0.800	1975	-0.882	-0.973
-0.979		-0.904		-0.919	1976	-0.829	-0.981
-0.585		-0.471		-0.506	1977	-0.331	-0.505
-0.616		-0.506		-0.553	1978	-0.294	-0.442
-0.405		-0.405	-0.421	-0.354	1979	-0.197	-0.326
-0.303	-0.222	-0.258	-0.261	-0.253	1980	-0.127	-0.243
-0.337	-0.268	-0.276	-0.293	-0.289	1981	-0.272	-0.380
-0.481	-0.511	-0.505	-0.462	-0.486	1982	-0.340	-0.448
-0.268	-0.315	-0.317	-0.212	-0.273	1983	-0.038	-0.111
-0.547	-0.552	-0.562	-0.455	-0.534	1984	-0.544	-0.597
-0.566	-0.600	-0.525	-0.527	-0.567	1985	-0.513	-0.573
-0.430	-0.509	-0.457	-0.386	-0.450	1986	-0.321	-0.422

-0.130	-0.228	-0.189	-0.096	-0.164	1987	0.126	0.034
-0.105	-0.138	-0.156	-0.117	-0.111	1988	-0.160	-0.231
-0.359	-0.403	-0.409	-0.349	-0.360	1989	-0.581	-0.637
-0.119	-0.185	-0.136	-0.143	-0.123	1990	-0.096	-0.158
-0.130	-0.201	-0.147	-0.118	-0.140	1991	-0.067	-0.138
-0.408	-0.464	-0.458	-0.408	-0.416	1992	-0.210	-0.269
-0.392	-0.421	-0.381	-0.356	-0.386	1993	-0.236	-0.284
-0.265	-0.292	-0.285	-0.224	-0.270	1994	-0.219	-0.257
-0.146	-0.166	-0.206	-0.099	-0.151	1995	-0.047	-0.078
-0.231	-0.272	-0.346	-0.193	-0.250	1996	-0.269	-0.299
-0.228	-0.244	-0.313	-0.182	-0.239	1997	-0.144	-0.192
0.260	0.221	0.202	0.292	0.234	1998	0.331	0.303
-0.215	-0.242	-0.272	-0.202	-0.246	1999	-0.532	-0.539
-0.243	-0.249	-0.301	-0.208	-0.269	2000	-0.388	-0.395
-0.063	-0.061	-0.129	-0.054	-0.085	2001	-0.173	-0.198
0.033	0.078	-0.007	0.049	0.037	2002	0.070	0.034
0.033	0.111	0.008	0.037	0.044	2003	0.067	0.036
-0.049	0.034	-0.087	-0.056	-0.040	2004	-0.037	-0.044
0.118	0.181	0.113	0.071	0.114	2005	0.131	0.158
0.018	0.058	0.016	-0.016	0.013	2006	-0.018	0.022
-0.005	0.056	0.050	0.026	0.022	2007	-0.056	-0.015
-0.252	-0.172	-0.231	-0.214	-0.221	2008	-0.424	-0.392
-0.049	-0.022	0.000	-0.025	-0.033	2009	0.095	0.123
0.223	0.186	0.174	0.215	0.220	2010	0.198	0.221
-0.071	-0.097	-0.093	-0.100	-0.081	2011	-0.341	-0.312
-0.036	-0.050	-0.027	-0.058	-0.041	2012	-0.098	-0.075
0.058	0.007	0.100	0.024	0.044	2013	0.052	0.080
0.092	0.074	0.140	0.075	0.093	2014	0.119	0.139
0.197	0.175	0.286	0.183	0.198	2015	0.333	0.346
0.463	0.427	0.587	0.411	0.463	2016	0.637	0.647
0.307	0.301	0.370	0.279	0.322	2017	0.311	0.331
0.172	0.188	0.260	0.127	0.198	2018	0.108	0.143
0.368	0.428	0.481	0.330	0.411	2019	0.424	0.463
0.433	0.434	0.491	0.392	0.454	2020	0.383	0.438
0.234	0.270	0.270	0.197	0.265	2021	0.013	0.085
0.282	0.341	0.272	0.199	0.308	2022	-0.014	-0.112
0.571	0.653	0.539	0.486	0.603	2023	0.502	0.581
0.884	0.973	0.886	0.806	0.924	2024	0.920	0.999
					2025		
0.198	0.216	0.215	0.176	0.202		0.155	0.190
0.182	0.183	0.261	0.148	0.197			

RATPAC	UAH	RSS4.0	NOAA	ERA5	JRA3Q	MERRA-2	Sonde Ave	Sat Avg
-0.098				-0.215	-0.357		-0.227	
-0.488				-0.487	-0.625		-0.493	
-0.489				-0.570	-0.691		-0.482	
-0.707				-0.686	-0.812		-0.707	
-0.631				-0.680	-0.761		-0.683	
-0.576				-0.598	-0.661		-0.586	
-0.715				-0.750	-0.750		-0.716	
-0.884				-0.776	-0.802		-0.855	
-0.471				-0.443	-0.532		-0.504	
-0.730				-0.771	-0.804		-0.737	
-0.637				-0.726	-0.793		-0.722	
-0.264				-0.205	-0.269		-0.254	
-0.398				-0.417	-0.503		-0.274	
-1.007				-1.008	-1.099		-1.062	
-0.570				-0.466	-0.540		-0.525	
-0.306				-0.305	-0.444		-0.335	
-0.868				-0.928	-1.000		-0.916	
-0.884				-0.921	-1.000		-0.913	
-0.921				-0.849	-0.937		-0.910	
-0.436				-0.388	-0.495		-0.424	
-0.422				-0.428	-0.505		-0.386	
-0.252	-0.359	-0.293		-0.148	-0.238		-0.258	-0.326
-0.159	-0.228	-0.210		-0.165	-0.234	-0.214	-0.176	-0.219
-0.271	-0.359	-0.378	-0.330	-0.333	-0.378	-0.371	-0.308	-0.356
-0.369	-0.372	-0.405	-0.278	-0.373	-0.349	-0.437	-0.386	-0.352
-0.055	0.029	-0.045	0.147	-0.018	-0.020	-0.162	-0.068	0.044
-0.538	-0.443	-0.565	-0.439	-0.552	-0.570	-0.674	-0.560	-0.482
-0.557	-0.585	-0.686	-0.483	-0.603	-0.605	-0.758	-0.548	-0.585
-0.452	-0.346	-0.463	-0.235	-0.400	-0.387	-0.581	-0.398	-0.348

0.103	0.179	0.069	0.325	0.126	0.137	-0.036	0.088	0.191
-0.168	-0.134	-0.241	-0.002	-0.119	-0.152	-0.182	-0.187	-0.126
-0.623	-0.554	-0.622	-0.413	-0.504	-0.563	-0.568	-0.614	-0.530
-0.189	-0.191	-0.281	-0.041	-0.099	-0.166	-0.198	-0.148	-0.171
-0.185	-0.124	-0.196	0.019	-0.089	-0.145	-0.160	-0.130	-0.100
-0.282	-0.308	-0.347	-0.160	-0.243	-0.273	-0.240	-0.254	-0.272
-0.297	-0.245	-0.296	-0.155	-0.212	-0.268	-0.222	-0.272	-0.232
-0.241	-0.167	-0.257	-0.114	-0.204	-0.223	-0.177	-0.239	-0.179
-0.080	0.005	-0.103	0.028	-0.040	-0.087	-0.065	-0.068	-0.023
-0.344	-0.153	-0.258	-0.183	-0.217	-0.266	-0.231	-0.304	-0.198
-0.245	-0.021	-0.105	-0.049	-0.089	-0.116	-0.020	-0.193	-0.058
0.333	0.548	0.408	0.483	0.447	0.444	0.492	0.322	0.480
-0.530	-0.384	-0.462	-0.451	-0.498	-0.452	-0.464	-0.534	-0.432
-0.441	-0.280	-0.366	-0.366	-0.428	-0.360	-0.363	-0.408	-0.337
-0.214	-0.106	-0.177	-0.168	-0.249	-0.160	-0.154	-0.195	-0.150
0.023	0.079	0.043	0.023	-0.034	0.038	0.071	0.042	0.048
0.076	0.109	0.088	0.060	0.017	0.094	0.156	0.060	0.086
0.031	-0.031	-0.004	-0.067	-0.112	-0.011	0.069	-0.017	-0.034
0.205	0.148	0.173	0.109	0.070	0.177	0.224	0.165	0.143
0.064	-0.046	-0.012	-0.069	-0.094	0.001	0.009	0.023	-0.042
0.013	-0.022	0.007	-0.045	-0.042	-0.063	-0.033	-0.019	-0.020
-0.368	-0.384	-0.310	-0.387	-0.358	-0.379	-0.356	-0.394	-0.360
0.046	0.029	0.086	0.022	0.061	0.039	0.017	0.088	0.046
0.350	0.221	0.248	0.225	0.286	0.253	0.167	0.256	0.231
-0.190	-0.272	-0.227	-0.261	-0.224	-0.224	-0.292	-0.281	-0.253
-0.089	-0.183	-0.113	-0.180	-0.136	-0.130	-0.194	-0.087	-0.159
0.084	-0.032	0.036	-0.016	0.059	0.054	-0.036	0.072	-0.004
0.087	0.015	0.080	0.026	0.087	0.081	0.020	0.115	0.040
0.327	0.222	0.309	0.252	0.315	0.300	0.242	0.336	0.261
0.627	0.497	0.540	0.503	0.588	0.557	0.486	0.637	0.513
0.290	0.201	0.253	0.200	0.300	0.245	0.207	0.311	0.218
0.112	0.010	0.102	0.030	0.134	0.072	0.055	0.121	0.047
0.442	0.332	0.434	0.336	0.458	0.397	0.411	0.443	0.367
0.393	0.345	0.423	0.354	0.449	0.419	0.384	0.405	0.374
0.137	-0.006	0.102	0.049	0.120	0.090	0.088	0.078	0.048
-0.070	-0.129	-0.054	-0.071	-0.014	-0.025	-0.009	-0.065	-0.085
0.482	0.433	0.497	0.469	0.550	0.547	0.594	0.522	0.466
0.939	0.923	0.946	0.909	1.016	0.997	1.066	0.953	0.926

0.175	0.141	0.182	0.122	0.165	0.169	0.187	0.173	0.148
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MT GL						
		RAOBCOR RICH	RATPAC A UNSW		UAH	
Reanal Avg	1955					
	1956					
	1957					
-0.286	1958	-0.165	-0.292	-0.254		
-0.556	1959	-0.228	-0.354	-0.338	-0.138	
-0.630	1960	-0.246	-0.373	-0.356	-0.214	
-0.749	1961	-0.251	-0.390	-0.325	-0.223	
-0.721	1962	-0.433	-0.549	-0.461	-0.331	
-0.630	1963	-0.290	-0.382	-0.336	-0.257	
-0.750	1964	-0.338	-0.438	-0.506	-0.307	
-0.789	1965	-0.608	-0.713	-0.659	-0.402	
-0.487	1966	-0.379	-0.481	-0.409	-0.247	
-0.788	1967	-0.410	-0.495	-0.457	-0.339	
-0.759	1968	-0.553	-0.629	-0.535	-0.434	
-0.237	1969	-0.309	-0.397	-0.293	-0.195	
-0.460	1970	-0.258	-0.309	-0.318	-0.203	
-1.053	1971	-0.645	-0.691	-0.611	-0.415	
-0.503	1972	-0.483	-0.547	-0.444	-0.343	
-0.374	1973	-0.151	-0.235	-0.204	-0.054	
-0.964	1974	-0.550	-0.615	-0.556	-0.340	
-0.961	1975	-0.467	-0.536	-0.490	-0.237	
-0.893	1976	-0.646	-0.748	-0.659	-0.445	
-0.441	1977	-0.227	-0.360	-0.202	-0.095	
-0.466	1978	-0.237	-0.372	-0.305	-0.175	
-0.193	1979	-0.195	-0.293	-0.161	-0.112	-0.213
-0.204	1980	-0.060	-0.156	-0.058	0.022	-0.062
-0.361	1981	-0.155	-0.237	-0.133	-0.070	-0.154
-0.386	1982	-0.238	-0.306	-0.209	-0.092	-0.230
-0.067	1983	-0.097	-0.147	-0.103	0.063	-0.034
-0.598	1984	-0.420	-0.481	-0.389	-0.196	-0.353
-0.655	1985	-0.427	-0.498	-0.388	-0.241	-0.402
-0.456	1986	-0.316	-0.402	-0.335	-0.193	-0.313

0.076	1987	-0.006	-0.090	-0.016	0.092	-0.009
-0.151	1988	-0.031	-0.074	-0.049	0.063	-0.038
-0.545	1989	-0.283	-0.298	-0.311	-0.128	-0.291
-0.154	1990	0.009	0.005	-0.060	0.109	-0.075
-0.131	1991	0.053	0.040	-0.040	0.117	-0.009
-0.252	1992	-0.207	-0.231	-0.269	-0.097	-0.222
-0.234	1993	-0.298	-0.325	-0.368	-0.140	-0.300
-0.202	1994	-0.226	-0.249	-0.231	-0.075	-0.183
-0.064	1995	-0.217	-0.238	-0.217	-0.065	-0.103
-0.238	1996	-0.320	-0.333	-0.331	-0.191	-0.163
-0.075	1997	-0.289	-0.299	-0.275	-0.118	-0.126
0.461	1998	0.235	0.230	0.202	0.367	0.324
-0.472	1999	-0.278	-0.283	-0.293	-0.096	-0.181
-0.383	2000	-0.318	-0.327	-0.315	-0.165	-0.206
-0.188	2001	-0.118	-0.145	-0.107	-0.001	-0.040
0.025	2002	0.010	-0.020	0.045	0.093	0.092
0.089	2003	0.007	-0.019	0.044	0.125	0.046
-0.018	2004	-0.070	-0.081	-0.043	0.034	-0.040
0.157	2005	0.058	0.061	0.110	0.140	0.048
-0.028	2006	-0.017	-0.008	0.035	0.087	-0.046
-0.046	2007	0.006	0.015	0.010	0.171	-0.007
-0.364	2008	-0.269	-0.263	-0.248	-0.084	-0.256
0.039	2009	-0.026	-0.024	-0.021	0.089	-0.041
0.235	2010	0.187	0.194	0.240	0.403	0.207
-0.247	2011	-0.126	-0.114	-0.097	0.085	-0.142
-0.153	2012	-0.061	-0.052	-0.024	0.095	-0.077
0.026	2013	0.106	0.114	0.119	0.249	0.044
0.063	2014	0.105	0.116	0.100	0.256	0.052
0.286	2015	0.245	0.257	0.260	0.403	0.141
0.544	2016	0.511	0.523	0.449		0.357
0.251	2017	0.297	0.317	0.279		0.215
0.087	2018	0.196	0.227	0.181		0.052
0.422	2019	0.382	0.419	0.382		0.263
0.418	2020	0.443	0.498	0.423		0.301
0.099	2021	0.172	0.238	0.209		0.063
-0.016	2022	0.201	0.204	0.217		0.066
0.564	2023	0.423	0.429	0.459		0.334
1.026	2024	0.857	0.864	0.881		0.722
	2025					

0.171		0.146	0.171	0.151	0.092	0.113
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RSS	NOAA	ERA5	JRA3Q	MERRA2	Sonde Ave	Sat Avg	Reanal Avg
		-0.132	-0.202		-0.237		
		-0.215	-0.331		-0.307		
		-0.353	-0.390		-0.325		
		-0.299	-0.393		-0.322		
		-0.438	-0.511		-0.481		
		-0.315	-0.395		-0.336		
		-0.404	-0.443		-0.427		
		-0.608	-0.623		-0.660		
		-0.326	-0.382		-0.423		
		-0.449	-0.513		-0.454		
		-0.529	-0.594		-0.573		
		-0.233	-0.288		-0.333		
		-0.324	-0.391		-0.295		
		-0.614	-0.686		-0.649		
		-0.456	-0.519		-0.491		
		-0.197	-0.300		-0.197		
		-0.600	-0.696		-0.574		
		-0.484	-0.600		-0.497		
		-0.625	-0.739		-0.684		
		-0.197	-0.330		-0.263		
		-0.243	-0.361		-0.304		
-0.317	-0.231	-0.114	-0.175		-0.216	-0.254	-0.144
-0.153	-0.072	-0.058	-0.088	-0.124	-0.091	-0.096	-0.090
-0.245	-0.149	-0.163	-0.190	-0.233	-0.175	-0.183	-0.195
-0.319	-0.235	-0.237	-0.240	-0.331	-0.251	-0.261	-0.269
-0.116	-0.024	-0.063	-0.074	-0.188	-0.116	-0.058	-0.108
-0.445	-0.357	-0.401	-0.397	-0.502	-0.430	-0.385	-0.433
-0.490	-0.386	-0.433	-0.420	-0.558	-0.438	-0.426	-0.471
-0.415	-0.283	-0.308	-0.290	-0.446	-0.351	-0.337	-0.348

-0.115	0.062	-0.013	0.020	-0.153	-0.037	-0.021	-0.049
-0.146	0.028	0.011	0.045	-0.066	-0.051	-0.052	-0.003
-0.405	-0.229	-0.248	-0.225	-0.344	-0.298	-0.308	-0.272
-0.178	-0.009	0.002	-0.005	-0.120	-0.015	-0.087	-0.041
-0.103	0.053	0.054	0.025	-0.072	0.018	-0.020	0.002
-0.291	-0.179	-0.163	-0.199	-0.261	-0.236	-0.231	-0.207
-0.367	-0.266	-0.299	-0.313	-0.381	-0.330	-0.311	-0.331
-0.242	-0.150	-0.223	-0.202	-0.283	-0.236	-0.191	-0.236
-0.169	-0.082	-0.176	-0.156	-0.225	-0.224	-0.118	-0.186
-0.220	-0.160	-0.268	-0.232	-0.309	-0.328	-0.181	-0.270
-0.173	-0.133	-0.239	-0.206	-0.263	-0.287	-0.144	-0.236
0.291	0.312	0.217	0.277	0.202	0.222	0.309	0.232
-0.188	-0.221	-0.288	-0.225	-0.269	-0.284	-0.197	-0.261
-0.204	-0.247	-0.341	-0.276	-0.300	-0.320	-0.219	-0.306
-0.021	-0.072	-0.152	-0.109	-0.079	-0.124	-0.044	-0.113
0.124	0.058	0.027	0.047	0.108	0.012	0.091	0.061
0.079	0.019	-0.015	0.015	0.101	0.011	0.048	0.034
-0.020	-0.070	-0.072	-0.042	0.052	-0.065	-0.043	-0.021
0.070	0.027	0.026	0.074	0.147	0.076	0.048	0.082
-0.023	-0.061	-0.038	-0.021	0.035	0.003	-0.043	-0.008
0.007	-0.019	0.000	-0.019	0.044	0.010	-0.006	0.008
-0.240	-0.263	-0.244	-0.263	-0.196	-0.260	-0.253	-0.235
-0.027	-0.050	-0.024	-0.053	-0.008	-0.024	-0.039	-0.029
0.218	0.196	0.269	0.238	0.223	0.207	0.207	0.243
-0.121	-0.138	-0.113	-0.118	-0.126	-0.112	-0.134	-0.119
-0.053	-0.078	-0.054	-0.052	-0.049	-0.045	-0.069	-0.052
0.067	0.037	0.105	0.086	0.068	0.113	0.049	0.086
0.080	0.058	0.108	0.075	0.085	0.107	0.063	0.089
0.174	0.151	0.202	0.173	0.180	0.254	0.155	0.185
0.387	0.366	0.435	0.396	0.387	0.494	0.370	0.406
0.245	0.223	0.302	0.268	0.262	0.298	0.228	0.278
0.088	0.077	0.152	0.113	0.135	0.201	0.072	0.133
0.296	0.280	0.378	0.325	0.393	0.395	0.280	0.365
0.336	0.331	0.435	0.372	0.400	0.455	0.323	0.402
0.107	0.125	0.209	0.152	0.200	0.206	0.098	0.187
0.105	0.131	0.214	0.204	0.257	0.208	0.101	0.225
0.374	0.408	0.492	0.464	0.555	0.437	0.372	0.504
0.758	0.773	0.908	0.853	0.969	0.867	0.751	0.910

0.152	0.114	0.143	0.134	0.182	0.156	0.126	0.150
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MT Tropics

	RAOB AVC	RAOBCOR	RICH	RATPAC A	UNSW	UAH	RSS	NOAA
1955								
1956								
1957								
1958	-0.262	-0.031	-0.253	-0.025				
1959	-0.289	-0.182	-0.533	-0.348	-0.310			
1960	-0.276	-0.256	-0.424	-0.391	-0.383			
1961	-0.391	-0.386	-0.603	-0.500	-0.366			
1962	-0.436	-0.485	-0.696	-0.481	-0.415			
1963	-0.294	-0.302	-0.477	-0.452	-0.298			
1964	-0.421	-0.337	-0.582	-0.451	-0.367			
1965	-0.700	-0.551	-0.798	-0.693	-0.402			
1966	-0.338	-0.213	-0.460	-0.276	-0.207			
1967	-0.506	-0.429	-0.634	-0.488	-0.400			
1968	-0.576	-0.567	-0.729	-0.527	-0.466			
1969	0.003	-0.058	-0.213	-0.142	-0.120			
1970	0.130	-0.005	-0.030	-0.238	-0.069			
1971	-0.943	-0.978	-1.003	-0.847	-0.472			
1972	-0.451	-0.435	-0.514	-0.429	-0.310			
1973	-0.135	-0.172	-0.297	-0.167	0.025			
1974	-0.729	-0.775	-0.885	-0.713	-0.419			
1975	-0.677	-0.756	-0.870	-0.678	-0.333			
1976	-0.707	-0.720	-0.912	-0.711	-0.368			
1977	-0.260	-0.262	-0.489	-0.285	-0.156			
1978	-0.191	-0.197	-0.396	-0.279	-0.102			
1979	-0.121	-0.189	-0.303	-0.105	-0.090	-0.186	-0.310	-0.161
1980	0.033	-0.082	-0.205	-0.020	0.078	-0.072	-0.189	-0.043
1981	-0.139	-0.243	-0.355	-0.165	-0.119	-0.231	-0.343	-0.183
1982	-0.107	-0.217	-0.304	-0.107	-0.069	-0.207	-0.318	-0.162
1983	0.234	0.098	0.057	0.170	0.249	0.173	0.074	0.240
1984	-0.461	-0.593	-0.637	-0.541	-0.219	-0.485	-0.606	-0.454
1985	-0.405	-0.524	-0.580	-0.493	-0.250	-0.512	-0.626	-0.462
1986	-0.259	-0.322	-0.435	-0.372	-0.202	-0.359	-0.476	-0.285

1987	0.298	0.189	0.088	0.217	0.207	0.205	0.091	0.317
1988	0.004	-0.133	-0.184	-0.078	0.062	-0.094	-0.216	0.002
1989	-0.363	-0.538	-0.547	-0.491	-0.166	-0.491	-0.613	-0.405
1990	0.096	0.002	-0.009	-0.017	0.151	-0.107	-0.214	-0.013
1991	0.131	0.027	-0.015	-0.031	0.100	-0.034	-0.135	0.054
1992	0.006	-0.084	-0.125	-0.164	0.017	-0.167	-0.247	-0.098
1993	-0.076	-0.200	-0.227	-0.247	-0.023	-0.191	-0.265	-0.139
1994	-0.106	-0.225	-0.247	-0.239	-0.097	-0.174	-0.246	-0.128
1995	0.057	-0.079	-0.106	-0.091	0.060	-0.001	-0.067	0.028
1996	-0.184	-0.365	-0.392	-0.398	-0.208	-0.208	-0.271	-0.203
1997	-0.027	-0.157	-0.205	-0.246	-0.064	-0.020	-0.065	-0.024
1998	0.554	0.365	0.337	0.368	0.423	0.541	0.507	0.524
1999	-0.270	-0.484	-0.490	-0.455	-0.258	-0.338	-0.348	-0.407
2000	-0.237	-0.421	-0.426	-0.430	-0.232	-0.306	-0.308	-0.373
2001	-0.043	-0.194	-0.225	-0.196	-0.132	-0.119	-0.104	-0.174
2002	0.123	0.011	-0.029	0.016	0.032	0.030	0.070	-0.002
2003	0.170	0.048	0.009	0.097	0.121	0.074	0.111	0.044
2004	0.098	-0.052	-0.064	0.011	0.038	-0.042	-0.014	-0.073
2005	0.268	0.079	0.102	0.178	0.100	0.087	0.111	0.065
2006	0.192	0.041	0.072	0.072	0.063	-0.029	-0.015	-0.057
2007	0.083	-0.068	-0.041	-0.019	0.083	-0.058	-0.046	-0.069
2008	-0.243	-0.424	-0.409	-0.415	-0.149	-0.369	-0.358	-0.382
2009	0.150	0.046	0.057	-0.002	0.070	-0.005	0.010	-0.015
2010	0.412	0.237	0.250	0.353	0.410	0.243	0.249	0.229
2011	-0.095	-0.276	-0.254	-0.182	0.095	-0.217	-0.211	-0.231
2012	-0.037	-0.175	-0.161	-0.190	-0.002	-0.215	-0.181	-0.208
2013	0.206	0.066	0.082	0.041	0.278	-0.003	0.028	-0.004
2014	0.232	0.113	0.121	0.057	0.279	0.017	0.049	0.023
2015	0.510	0.383	0.390	0.346	0.488	0.266	0.302	0.275
2016	0.675	0.576	0.580	0.562		0.446	0.484	0.465
2017	0.383	0.273	0.297	0.246		0.163	0.204	0.185
2018	0.222	0.106	0.157	0.101		-0.006	0.038	0.020
2019	0.409	0.381	0.437	0.408		0.276	0.322	0.305
2020		0.451	0.523	0.448		0.358	0.395	0.371
2021		0.087	0.179	0.213		0.029	0.075	0.070
2022		0.080	0.055	0.021		-0.062	-0.031	-0.027
2023		0.512	0.554	0.499		0.407	0.447	0.464
2024		0.966	1.008	0.957		0.855	0.895	0.902
2025								

	0.121	0.147	0.178	0.139	0.074	0.113	0.158	0.102
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UW	ERA-I	ERA5	JRA3Q	MERRA2	Sonde Avg	Sat Avg	Reanal Avg
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		-0.055	-0.139		-0.103		
		-0.270	-0.367		-0.354		
		-0.431	-0.516		-0.357		
		-0.441	-0.552		-0.496		
		-0.520	-0.577		-0.554		
		-0.386	-0.448		-0.410		
		-0.475	-0.500		-0.457		
		-0.655	-0.674		-0.681		
		-0.286	-0.347		-0.316		
		-0.569	-0.601		-0.517		
		-0.612	-0.678		-0.608		
		-0.084	-0.121		-0.138		
		-0.329	-0.373		-0.091		
		-0.919	-0.983		-0.943		
		-0.445	-0.480		-0.459		
		-0.209	-0.301		-0.212		
		-0.830	-0.895		-0.791		
		-0.784	-0.872		-0.768		
		-0.694	-0.800		-0.781		
		-0.295	-0.403		-0.345		
		-0.265	-0.353		-0.291		
-0.171	0.082	-0.109	-0.152		-0.199	-0.219	-0.130
-0.045	0.093	-0.074	-0.116	-0.163	-0.102	-0.101	-0.118
-0.191	-0.086	-0.250	-0.272	-0.319	-0.255	-0.252	-0.280
-0.174	-0.081	-0.235	-0.221	-0.315	-0.210	-0.229	-0.257
0.210	0.239	0.130	0.128	-0.024	0.108	0.162	0.078
-0.473	-0.376	-0.580	-0.582	-0.727	-0.590	-0.515	-0.630
-0.469	-0.390	-0.565	-0.550	-0.761	-0.533	-0.533	-0.625
-0.311	-0.228	-0.382	-0.364	-0.596	-0.377	-0.373	-0.447

0.274	0.289	0.189	0.203	-0.014	0.165	0.204	0.126
-0.038	0.044	-0.058	-0.064	-0.138	-0.132	-0.103	-0.086
-0.443	-0.366	-0.452	-0.458	-0.511	-0.525	-0.503	-0.474
-0.040	0.047	-0.005	-0.031	-0.080	-0.008	-0.111	-0.039
0.031	0.080	0.018	-0.029	-0.052	-0.006	-0.038	-0.021
-0.090	-0.099	-0.109	-0.144	-0.105	-0.124	-0.171	-0.119
-0.106	-0.106	-0.172	-0.203	-0.168	-0.225	-0.198	-0.181
-0.087	-0.115	-0.225	-0.222	-0.203	-0.237	-0.183	-0.217
0.106	0.061	-0.045	-0.042	-0.038	-0.092	-0.013	-0.041
-0.097	-0.160	-0.305	-0.301	-0.280	-0.385	-0.227	-0.295
0.106	0.026	-0.109	-0.085	-0.016	-0.202	-0.036	-0.070
0.686	0.529	0.460	0.499	0.536	0.356	0.524	0.498
-0.206	-0.316	-0.435	-0.380	-0.402	-0.477	-0.364	-0.405
-0.161	-0.246	-0.442	-0.373	-0.393	-0.426	-0.329	-0.403
0.041	-0.043	-0.252	-0.196	-0.180	-0.205	-0.132	-0.209
0.217	0.118	-0.062	-0.038	0.012	-0.001	0.033	-0.029
0.248	0.182	-0.003	0.032	0.107	0.051	0.076	0.045
0.137	0.093	-0.095	-0.054	0.038	-0.035	-0.043	-0.037
0.267	0.263	0.039	0.087	0.149	0.119	0.088	0.091
0.139	0.176	-0.025	0.006	0.025	0.062	-0.034	0.002
0.092	0.114	-0.057	-0.077	-0.059	-0.042	-0.058	-0.065
-0.215	-0.197	-0.342	-0.367	-0.357	-0.416	-0.370	-0.355
0.153	0.162	0.017	-0.009	-0.020	0.034	-0.003	-0.004
0.392	0.386	0.317	0.280	0.207	0.280	0.240	0.268
-0.072	-0.064	-0.175	-0.176	-0.239	-0.237	-0.220	-0.196
-0.051	-0.043	-0.213	-0.207	-0.259	-0.175	-0.201	-0.226
0.147	0.185	0.060	0.050	-0.023	0.063	0.007	0.029
0.163	0.213	0.076	0.057	0.010	0.097	0.030	0.048
0.402	0.474	0.345	0.334	0.290	0.373	0.281	0.323
0.604	0.675	0.513	0.486	0.427	0.573	0.465	0.475
0.325	0.467	0.254	0.226	0.175	0.272	0.184	0.218
0.174	0.343	0.085	0.053	0.028	0.121	0.017	0.055
0.466		0.380	0.341	0.357	0.409	0.301	0.360
		0.499	0.456	0.437	0.474	0.375	0.464
		0.190	0.150	0.148	0.160	0.058	0.162
		0.100	0.094	0.090	0.052	-0.040	0.095
		0.580	0.568	0.607	0.522	0.439	0.585
		1.040	0.993	1.067	0.977	0.884	1.033
0.131	0.110	0.148	0.144	0.173	0.155	0.124	0.152

300-200 Tropics

	RAOBCOR	RICH	RATPAC A	ERA-I	ERA5	JRA55	MERRA2
1955							
1956							
1957							
1958	0.208	-0.06917	-0.112				
1959	-0.057	-0.2125	-0.596				
1960	-0.185	-0.25417	-0.509				
1961	-0.530	-0.55917	-0.682				
1962	-0.463	-0.47125	-0.519				
1963	-0.371	-0.38083	-0.632				
1964	-0.603	-0.56208	-0.622				
1965	-0.964	-0.93417	-0.792				
1966	-0.448	-0.42042	-0.216				
1967	-0.773	-0.71958	-0.579				
1968	-0.765	-0.7925	-0.662				
1969	0.042	-0.00167	-0.106				
1970	0.148	0.314583	-0.192				
1971	-1.394	-1.19333	-1.106				
1972	-0.566	-0.5175	-0.392				
1973	-0.118	-0.05	-0.139				
1974	-0.971	-0.81292	-0.846				
1975	-1.013	-0.83583	-0.812				
1976	-0.974	-0.99042	-0.812				
1977	-0.198	-0.28375	-0.149				
1978	-0.146	-0.20125	-0.229				
1979	-0.055	-0.08708	0.081	0.137	0.111		
1980	0.087	0.03	0.121	0.09	0.068		
1981	-0.227	-0.31917	-0.139	-0.207	-0.225		
1982	-0.240	-0.34625	-0.099	-0.32	-0.281		
1983	0.269	0.2275	0.244	0.188	0.268		
1984	-0.715	-0.74667	-0.722	-0.705	-0.709		
1985	-0.595	-0.64	-0.626	-0.727	-0.695		
1986	-0.207	-0.23292	-0.286	-0.376	-0.291		

1987	0.533	0.500417	0.581	0.472	0.545
1988	0.040	0.051667	0.104	0.069	0.122
1989	-0.592	-0.53375	-0.406	-0.547	-0.515
1990	0.092	0.120417	0.218	0.047	0.11
1991	0.170	0.11125	0.164	0.117	0.17
1992	-0.087	-0.15708	-0.146	-0.172	-0.08
1993	-0.099	-0.17458	-0.219	-0.208	-0.111
1994	-0.031	-0.13125	-0.159	-0.15	-0.08
1995	0.125	0.101667	0.028	0.11	0.132
1996	-0.150	-0.17958	-0.406	-0.18	-0.185
1997	0.154	0.057917	-0.059	0.146	0.162
1998	0.906	0.97375	0.741	0.934	0.964
1999	-0.459	-0.34542	-0.486	-0.376	-0.473
2000	-0.323	-0.19958	-0.426	-0.289	-0.495
2001	-0.056	0.037083	-0.106	0.022	-0.222
2002	0.307	0.350417	0.278	0.263	0.197
2003	0.328	0.3775	0.374	0.311	0.242
2004	0.185	0.239167	0.234	0.195	0.126
2005	0.432	0.54375	0.531	0.486	0.374
2006	0.186	0.37	0.278	0.327	0.202
2007	0.065	0.262917	0.188	0.201	0.198
2008	-0.579	-0.37208	-0.512	-0.376	-0.326
2009	0.138	0.319583	0.194	0.234	0.281
2010	0.389	0.555	0.641	0.622	0.669
2011	-0.328	-0.17917	-0.166	-0.111	-0.073
2012	-0.167	-0.01542	-0.119	-0.078	-0.052
2013	0.176	0.329583	0.214	0.289	0.31
2014	0.300	0.43375	0.281	0.352	0.387
2015	0.628	0.73375	0.644	0.707	0.71
2016	0.995	1.095833	1.051	1.057	1.046
2017	0.496	0.605417	0.538	0.447	0.548
2018	0.275	0.4075	0.307667	0.151	0.325
2019	0.752	0.881667	0.837667		

0.151	0.216	0.164	0.171	0.168	#DIV/0!	#DIV/0!
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		300-150 Tropics		
Sonde Ave	Reanalyses	RAOBCORE	RICH	RATPAC A
		1955		
		1956		
		1957		
0.009		1958	0.336875	0.02625
-0.288		1959	0.0715625	-0.13625
-0.316		1960	-0.0813542	-0.2227083
-0.590		1961	-0.4471875	-0.505625
-0.484		1962	-0.37	-0.4173958
-0.461		1963	-0.3263542	-0.3891667
-0.596		1964	-0.5069792	-0.5215625
-0.897		1965	-0.8857292	-0.89625
-0.361		1966	-0.4047917	-0.4096875
-0.691		1967	-0.6953125	-0.6667708
-0.740		1968	-0.7072917	-0.7489583
-0.022		1969	0.01802083	-0.0364583
0.090		1970	0.221875	0.3009375
-1.231		1971	-1.2984375	-1.1929167
-0.492		1972	-0.5988542	-0.6325
-0.102		1973	-0.1235417	-0.1077083
-0.877		1974	-0.8926042	-0.7869792
-0.887		1975	-0.9366667	-0.8064583
-0.926		1976	-0.9136458	-0.9090625
-0.210		1977	-0.2307292	-0.2928125
-0.192		1978	-0.1497917	-0.1957292
-0.020	0.124	1979	-0.0586458	-0.0792708
0.079	0.079	1980	0.048125	0.00645833
-0.228	-0.216	1981	-0.22125	-0.294375
-0.229	-0.3005	1982	-0.2248958	-0.3065625
0.247	0.228	1983	0.26604167	0.23729167
-0.728	-0.707	1984	-0.7134375	-0.731875
-0.620	-0.711	1985	-0.5903125	-0.6447917
-0.242	-0.3335	1986	-0.19625	-0.2384375

0.538	0.5085	1987	0.50739583	0.4578125
0.065	0.0955	1988	0.05302083	0.05666667
-0.511	-0.531	1989	-0.5178125	-0.4369792
0.143	0.0785	1990	0.12770833	0.1978125
0.149	0.1435	1991	0.20104167	0.18885417
-0.130	-0.126	1992	-0.05	-0.0815625
-0.164	-0.1595	1993	-0.0991667	-0.1584375
-0.107	-0.115	1994	-0.0135417	-0.1034375
0.085	0.121	1995	0.13770833	0.08479167
-0.245	-0.1825	1996	-0.1130208	-0.1892708
0.051	0.154	1997	0.19822917	0.06885417
0.874	0.949	1998	0.89947917	0.91385417
-0.430	-0.4245	1999	-0.4115625	-0.3505208
-0.316	-0.392	2000	-0.306875	-0.2221875
-0.041	-0.1	2001	-0.0627083	0.01552083
0.312	0.23	2002	0.25770833	0.3028125
0.360	0.2765	2003	0.24895833	0.30645833
0.220	0.1605	2004	0.13760417	0.20125
0.502	0.43	2005	0.3728125	0.49614583
0.278	0.2645	2006	0.09510417	0.29145833
0.172	0.1995	2007	-0.0069792	0.20552083
-0.488	-0.351	2008	-0.6084375	-0.3832292
0.217	0.2575	2009	0.04802083	0.24947917
0.528	0.6455	2010	0.33083333	0.51229167
-0.224	-0.092	2011	-0.3404167	-0.1714583
-0.101	-0.065	2012	-0.2344792	-0.0519792
0.240	0.2995	2013	0.0928125	0.26677083
0.338	0.3695	2014	0.2065625	0.3653125
0.669	0.7085	2015	0.51354167	0.6459375
1.047	1.0515	2016	0.86322917	0.98875
0.546	0.4975	2017	0.371875	0.5028125
0.330	0.238	2018	0.18583333	0.33020833
0.824		2019	0.61114583	0.751875
		2020		
		2021		
		2022		
		2023		
		2024		
		2025		

0.177	0.170	#DIV/0!	10.000	0.116	0.184	#DIV/0!
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ERA-I	ERA5	JRA55	MERRA2	Sonde Ave	Reanalyses
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0.182

-0.032

-0.152

-0.476

-0.394

-0.358

-0.514

-0.891

-0.407

-0.681

-0.728

-0.009

0.261

-1.246

-0.616

-0.116

-0.840

-0.872

-0.911

-0.262

-0.173

0.015

-0.069

0.015

0.027

0.027

0.027

-0.212

-0.258

-0.212

-0.293

-0.266

-0.293

0.237

0.252

0.237

-0.716

-0.723

-0.716

-0.661

-0.618

-0.661

-0.273

-0.217

-0.273

0.495	0.483	0.495
0.124	0.055	0.124
-0.493	-0.477	-0.493
0.104	0.163	0.104
0.183	0.195	0.183
-0.061	-0.066	-0.061
-0.119	-0.129	-0.119
-0.086	-0.058	-0.086
0.118	0.111	0.118
-0.193	-0.151	-0.193
0.151	0.134	0.151
0.912	0.907	0.912
-0.429	-0.381	-0.429
-0.49	-0.265	-0.49
-0.21	-0.024	-0.21
0.177	0.280	0.177
0.206	0.278	0.206
0.113	0.169	0.113
0.347	0.434	0.347
0.178	0.193	0.178
0.225	0.099	0.225
-0.283	-0.496	-0.283
0.288	0.149	0.288
0.682	0.422	0.682
-0.024	-0.256	-0.024
-0.031	-0.143	-0.031
0.315	0.180	0.315
0.375	0.286	0.375
0.698	0.580	0.698
1	0.926	1
0.514	0.437	0.514
0.312	0.258	0.312
	0.682	

#DIV/0!	0.172	#DIV/0!	#DIV/0!	0.150	0.172	#DIV/0!
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250-100

	RAOBCORE RICH	RATPAC A	ERA-I	ERA5	JRA55	MERRA2
1955						
1956						
1957						
1958	0.614	0.334				
1959	0.432	0.159				
1960	0.111	-0.122				
1961	0.002	-0.137				
1962	-0.087	-0.222				
1963	0.033	-0.129				
1964	-0.010	-0.138				
1965	-0.449	-0.538				
1966	-0.169	-0.261				
1967	-0.319	-0.344				
1968	-0.472	-0.527				
1969	0.050	-0.018				
1970	0.417	0.337				
1971	-0.922	-0.995				
1972	-0.599	-0.768				
1973	-0.024	-0.142				
1974	-0.637	-0.683				
1975	-0.644	-0.660				
1976	-0.639	-0.592				
1977	-0.271	-0.257				
1978	-0.161	-0.164				
1979	-0.083	-0.049		-0.077		
1980	-0.053	-0.055		-0.005		
1981	-0.172	-0.197		-0.082		
1982	-0.029	-0.060		-0.099		
1983	0.391	0.378		0.394		
1984	-0.583	-0.586		-0.541		
1985	-0.511	-0.564		-0.504		
1986	-0.253	-0.291		-0.221		

1987	0.382	0.324			0.359
1988	0.078	0.056			0.187
1989	-0.306	-0.198			-0.365
1990	0.207	0.336			0.131
1991	0.295	0.354			0.262
1992	0.093	0.112			0.052
1993	0.066	0.029			0.021
1994	0.029	-0.046			-0.091
1995	0.150	0.025			0.099
1996	-0.132	-0.267			-0.279
1997	0.202	0.078			0.016
1998	0.802	0.736			0.694
1999	-0.220	-0.261			-0.212
2000	-0.298	-0.299			-0.456
2001	-0.179	-0.134			-0.332
2002	-0.020	0.037			-0.048
2003	0.049	0.115			0.034
2004	-0.029	0.041			-0.048
2005	0.127	0.236			0.139
2006	-0.034	0.126			0.072
2007	-0.152	0.010			0.193
2008	-0.520	-0.368			-0.171
2009	-0.131	-0.002			0.221
2010	0.227	0.345			0.578
2011	-0.221	-0.100			0.106
2012	-0.386	-0.219			-0.107
2013	-0.073	0.100			0.197
2014	-0.033	0.124			0.290
2015	0.279	0.425			0.550
2016	0.432	0.566			0.692
2017	0.111	0.246			0.398
2018	0.000	0.124			0.221
2019	0.338	0.457			
2020					
2021					
2022					
2023					
2024					
2025					

10.000	0.029	0.081	#DIV/0!	#DIV/0!	0.110	#DIV/0!	#DIV/0!
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		TTT			RAOBCOF RICH		RATPAC / ERA-I		ERA5	
Sonde Ave	Reanalyses				RAOBCOF RICH		RATPAC / UAH		RSSv4.0	
		1955								
		1956								
		1957								
0.474		1958			0.038	-0.101	0.024			
0.295		1959			-0.200	-0.245	-0.385			
-0.005		1960			-0.276	-0.286	-0.369			
-0.067		1961			-0.482	-0.591	-0.560			
-0.154		1962			-0.466	-0.503	-0.459			
-0.048		1963			-0.391	-0.413	-0.507			
-0.074		1964			-0.536	-0.594	-0.540			
-0.494		1965			-0.788	-0.966	-0.719			
-0.215		1966			-0.398	-0.452	-0.286			
-0.331		1967			-0.605	-0.752	-0.532			
-0.500		1968			-0.629	-0.825	-0.520			
0.016		1969			0.017	-0.034	-0.111			
0.377		1970			0.047	0.283	-0.199			
-0.959		1971			-1.090	-1.225	-0.915			
-0.684		1972			-0.459	-0.550	-0.380			
-0.083		1973			-0.137	-0.082	-0.124			
-0.660		1974			-0.815	-0.845	-0.695			
-0.652		1975			-0.796	-0.868	-0.702			
-0.615		1976			-0.782	-1.022	-0.722			
-0.264		1977			-0.212	-0.316	-0.202			
-0.163		1978			-0.188	-0.233	-0.238			
-0.066	-0.077	1979			-0.093	-0.119	-0.029	-0.104	-0.169	
-0.054	-0.005	1980			0.045	-0.002	0.023	-0.013	-0.075	
-0.184	-0.082	1981			-0.171	-0.351	-0.099	-0.172	-0.232	
-0.044	-0.099	1982			-0.202	-0.378	-0.170	-0.218	-0.281	
0.385	0.394	1983			0.180	0.195	0.200	0.207	0.160	
-0.585	-0.541	1984			-0.507	-0.779	-0.456	-0.408	-0.480	
-0.538	-0.504	1985			-0.453	-0.672	-0.461	-0.475	-0.539	
-0.272	-0.221	1986			-0.231	-0.265	-0.267	-0.252	-0.320	

0.353	0.359		1987	0.328	0.468	0.347	0.348	0.281
0.067	0.187		1988	0.017	0.020	0.048	0.015	-0.060
-0.252	-0.365		1989	-0.452	-0.566	-0.449	-0.464	-0.541
0.271	0.131		1990	0.026	0.088	0.023	-0.062	-0.125
0.325	0.262		1991	0.086	0.079	0.032	0.025	-0.031
0.103	0.052		1992	-0.116	-0.189	-0.132	-0.177	-0.211
0.047	0.021		1993	-0.096	-0.207	-0.132	-0.127	-0.150
-0.008	-0.091		1994	-0.061	-0.163	-0.071	-0.041	-0.062
0.088	0.099		1995	0.099	0.070	0.080	0.125	0.108
-0.199	-0.279		1996	-0.119	-0.212	-0.216	-0.050	-0.065
0.140	0.016		1997	0.040	0.026	-0.086	0.114	0.116
0.769	0.694		1998	0.657	0.942	0.578	0.748	0.757
-0.240	-0.212		1999	-0.334	-0.377	-0.400	-0.297	-0.257
-0.298	-0.456		2000	-0.222	-0.232	-0.306	-0.197	-0.148
-0.157	-0.332		2001	-0.009	0.005	-0.075	-0.002	0.066
0.008	-0.048		2002	0.231	0.318	0.205	0.208	0.302
0.082	0.034		2003	0.257	0.345	0.280	0.245	0.338
0.006	-0.048		2004	0.153	0.207	0.187	0.102	0.185
0.182	0.139		2005	0.357	0.512	0.422	0.303	0.379
0.046	0.072		2006	0.170	0.338	0.223	0.089	0.157
-0.071	0.193		2007	0.114	0.231	0.200	0.115	0.175
-0.444	-0.171		2008	-0.327	-0.404	-0.294	-0.288	-0.224
-0.067	0.221		2009	0.177	0.288	0.222	0.176	0.239
0.286	0.578		2010	0.412	0.523	0.564	0.411	0.465
-0.160	0.106		2011	-0.172	-0.211	-0.036	-0.125	-0.068
-0.303	-0.107		2012	-0.026	-0.047	0.020	-0.043	0.044
0.013	0.197		2013	0.197	0.298	0.222	0.137	0.221
0.046	0.290		2014	0.268	0.402	0.281	0.187	0.269
0.352	0.550		2015	0.517	0.702	0.538	0.407	0.498
0.499	0.692		2016	0.812	1.064	0.866	0.702	0.793
0.178	0.398		2017	0.465	0.573	0.477	0.352	0.438
0.062	0.221		2018	0.275	0.375	0.299	0.169	0.261
0.398			2019	0.624	0.850	0.684	0.511	0.617
			2020					
			2021					
			2022					
			2023					
			2024					
			2025					

0.055	0.110	#DIV/0!	10.000	0.147	0.216	0.160	0.128	0.179
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0.98587 1 0.97852 0.97511 0.93924

JRA55 MERRA2 Sonde Av Reanalyses

NOAA UW ERA5 JRA55 MERRA2 Sonde Av Sat Avg Reanalyses Avg

			-0.092		-0.013		
			-0.395		-0.277		
			-0.424		-0.310		
			-0.598		-0.544		
			-0.558		-0.476		
			-0.509		-0.437		
			-0.670		-0.557		
			-0.718		-0.824		
			-0.388		-0.379		
			-0.672		-0.629		
			-0.590		-0.658		
			-0.052		-0.043		
			-0.231		0.043		
			-0.918		-1.077		
			-0.317		-0.463		
			-0.143		-0.114		
			-0.767		-0.785		
			-0.764		-0.789		
			-0.690		-0.842		
			-0.182		-0.243		
			-0.243		-0.220		
-0.245	-0.204	-0.009	-0.018		-0.080	-0.186	-0.013
-0.171	-0.103	-0.006	0.014	-0.043	0.022	-0.089	-0.011
-0.285	-0.245	-0.180	-0.160	-0.201	-0.207	-0.238	-0.180
-0.338	-0.300	-0.238	-0.212	-0.295	-0.250	-0.291	-0.248
0.102	0.128	0.175	0.146	0.033	0.192	0.144	0.118
-0.556	-0.517	-0.483	-0.445	-0.531	-0.581	-0.499	-0.487
-0.589	-0.542	-0.512	-0.476	-0.612	-0.529	-0.541	-0.534
-0.367	-0.313	-0.255	-0.231	-0.408	-0.254	-0.316	-0.298

0.255	0.308	0.333	0.332	0.169	0.381	0.294	0.278
-0.096	-0.043	0.067	0.017	0.033	0.028	-0.052	0.039
-0.588	-0.529	-0.395	-0.452	-0.407	-0.489	-0.535	-0.418
-0.161	-0.107	0.061	-0.024	-0.014	0.046	-0.116	0.007
-0.067	-0.019	0.091	0.025	0.039	0.066	-0.025	0.051
-0.247	-0.207	-0.097	-0.168	-0.083	-0.146	-0.209	-0.116
-0.185	-0.142	-0.063	-0.122	-0.040	-0.145	-0.146	-0.075
-0.087	-0.051	-0.048	-0.034	0.033	-0.098	-0.056	-0.016
0.095	0.133	0.122	0.091	0.145	0.083	0.116	0.119
-0.089	-0.041	-0.103	-0.106	-0.037	-0.182	-0.058	-0.082
0.100	0.136	0.077	0.076	0.166	-0.007	0.115	0.107
0.765	0.793	0.703	0.711	0.778	0.726	0.761	0.731
-0.281	-0.269	-0.354	-0.319	-0.315	-0.371	-0.275	-0.329
-0.170	-0.156	-0.311	-0.215	-0.210	-0.253	-0.163	-0.245
0.052	0.056	-0.114	-0.030	-0.004	-0.026	0.054	-0.049
0.306	0.295	0.162	0.226	0.260	0.251	0.298	0.216
0.357	0.317	0.209	0.261	0.323	0.294	0.328	0.265
0.246	0.179	0.082	0.130	0.209	0.182	0.182	0.140
0.480	0.376	0.279	0.366	0.419	0.430	0.377	0.355
0.268	0.156	0.121	0.145	0.153	0.243	0.157	0.139
0.280	0.158	0.153	0.114	0.142	0.181	0.167	0.136
-0.116	-0.232	-0.228	-0.283	-0.262	-0.342	-0.228	-0.258
0.339	0.226	0.237	0.194	0.157	0.229	0.233	0.196
0.577	0.451	0.510	0.443	0.360	0.500	0.458	0.438
0.040	-0.086	-0.054	-0.100	-0.159	-0.140	-0.077	-0.104
0.121	0.015	0.000	-0.003	-0.057	-0.018	0.029	-0.020
0.288	0.180	0.231	0.189	0.113	0.239	0.200	0.178
0.324	0.221	0.287	0.249	0.187	0.317	0.245	0.241
0.552	0.437	0.533	0.474	0.405	0.586	0.468	0.470
0.874	0.751	0.817	0.819	0.694	0.914	0.772	0.777
0.522	0.398	0.488	0.438	0.374	0.505	0.418	0.433
0.359	0.232	0.297	0.264	0.215	0.316	0.246	0.258
0.650	0.568	0.659	0.612	0.601	0.719	0.592	0.624

0.226	0.170	0.154	0.147	0.157	0.174	0.174	0.150
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#DIV/0! #DIV/0! 0.99272 0.9854

LT Global

	RAOBCOR	RICH17	RATPAC	UAHv6.0	RSSv4.0	Avg Sat	ERA-I	ERA5
1958	-0.400	-0.410	-0.288					
1959	-0.454	-0.466	-0.380					
1960	-0.474	-0.507	-0.392					
1961	-0.388	-0.465	-0.345					
1962	-0.473	-0.557	-0.477					
1963	-0.451	-0.540	-0.460					
1964	-0.600	-0.680	-0.709					
1965	-0.741	-0.820	-0.727					
1966	-0.511	-0.589	-0.498					
1967	-0.488	-0.563	-0.507					
1968	-0.635	-0.726	-0.572					
1969	-0.352	-0.446	-0.361					
1970	-0.324	-0.387	-0.356					
1971	-0.696	-0.747	-0.644					
1972	-0.546	-0.600	-0.470					
1973	-0.240	-0.285	-0.207					
1974	-0.599	-0.621	-0.565					
1975	-0.574	-0.586	-0.519					
1976	-0.753	-0.780	-0.704					
1977	-0.294	-0.335	-0.230					
1978	-0.337	-0.368	-0.323					
1979	-0.226	-0.250	-0.189	-0.209	-0.280	-0.244	-0.030	-0.146
1980	-0.082	-0.114	-0.060	-0.041	-0.128	-0.085	0.020	-0.065
1981	-0.099	-0.124	-0.067	-0.111	-0.143	-0.127	-0.036	-0.084
1982	-0.307	-0.334	-0.295	-0.296	-0.344	-0.320	-0.236	-0.286
1983	-0.094	-0.111	-0.140	-0.041	-0.112	-0.077	-0.028	-0.060
1984	-0.370	-0.389	-0.351	-0.237	-0.375	-0.306	-0.287	-0.321
1985	-0.322	-0.356	-0.310	-0.361	-0.430	-0.396	-0.312	-0.361
1986	-0.238	-0.285	-0.265	-0.219	-0.313	-0.266	-0.213	-0.241

1987	0.020	-0.012	-0.015	0.050	-0.017	0.016	0.047	0.020
1988	0.027	0.022	0.022	0.039	-0.048	-0.005	0.076	0.071
1989	-0.211	-0.196	-0.224	-0.209	-0.251	-0.230	-0.207	-0.150
1990	0.018	0.041	0.009	0.013	-0.075	-0.031	0.041	0.103
1991	0.025	0.037	-0.030	0.021	-0.029	-0.004	0.026	0.079
1992	-0.314	-0.314	-0.293	-0.280	-0.302	-0.291	-0.298	-0.203
1993	-0.214	-0.227	-0.224	-0.202	-0.238	-0.220	-0.267	-0.178
1994	-0.110	-0.139	-0.070	-0.064	-0.102	-0.083	-0.144	-0.088
1995	-0.021	-0.040	0.028	0.070	0.038	0.054	-0.029	0.032
1996	-0.116	-0.135	-0.153	-0.009	-0.062	-0.036	-0.126	-0.080
1997	-0.079	-0.110	-0.100	-0.007	-0.026	-0.016	-0.105	-0.066
1998	0.458	0.458	0.377	0.484	0.440	0.462	0.346	0.371
1999	-0.029	-0.026	-0.075	-0.017	-0.026	-0.021	-0.119	-0.102
2000	-0.073	-0.072	-0.105	-0.020	-0.032	-0.026	-0.094	-0.128
2001	0.096	0.087	0.094	0.115	0.137	0.126	0.096	0.050
2002	0.218	0.208	0.192	0.217	0.247	0.232	0.195	0.193
2003	0.208	0.203	0.244	0.187	0.263	0.225	0.218	0.187
2004	0.137	0.136	0.143	0.080	0.188	0.134	0.131	0.095
2005	0.313	0.327	0.355	0.199	0.323	0.261	0.331	0.247
2006	0.195	0.223	0.283	0.114	0.235	0.175	0.274	0.173
2007	0.246	0.282	0.266	0.160	0.273	0.216	0.235	0.200
2008	-0.062	-0.018	0.021	-0.101	0.065	-0.018	-0.042	-0.043
2009	0.164	0.213	0.228	0.094	0.235	0.165	0.150	0.160
2010	0.374	0.419	0.454	0.331	0.482	0.407	0.375	0.411
2011	0.064	0.108	0.182	0.016	0.155	0.085	0.076	0.109
2012	0.144	0.190	0.238	0.053	0.211	0.132	0.105	0.151
2013	0.274	0.320	0.357	0.137	0.280	0.209	0.217	0.248
2014	0.307	0.352	0.383	0.182	0.334	0.258	0.251	0.287
2015	0.436	0.475	0.524	0.275	0.459	0.367	0.362	0.401
2016	0.745	0.783	0.766	0.526	0.648	0.587	0.636	0.662
2017	0.546	0.585	0.598	0.403	0.529	0.466	0.452	0.536
2018	0.429	0.468	0.466	0.226	0.389	0.307	0.301	0.413
2019	0.649568	0.687508	0.683475	0.441	0.593467	0.517234		0.612485
79-19	0.187	0.208	0.208	0.132	0.208	0.170	0.142	0.168
95-19	0.227	0.258	0.272	0.109	0.202	0.156	0.186	0.225

					LT Tropics		
JRA	MERRA	Sonde Ave	Sat Avg	Reanal Avg	RAOBCOR RICH		
-0.236		-0.366		-0.236	1958	-0.045	-0.138
-0.354		-0.434		-0.354	1959	-0.317	-0.438
-0.406		-0.458		-0.406	1960	-0.380	-0.492
-0.416		-0.399		-0.416	1961	-0.572	-0.673
-0.493		-0.502		-0.493	1962	-0.529	-0.645
-0.465		-0.484		-0.465	1963	-0.469	-0.595
-0.608		-0.663		-0.608	1964	-0.610	-0.725
-0.660		-0.763		-0.660	1965	-0.780	-0.891
-0.427		-0.533		-0.427	1966	-0.424	-0.516
-0.529		-0.520		-0.529	1967	-0.631	-0.716
-0.574		-0.644		-0.574	1968	-0.620	-0.777
-0.260		-0.386		-0.260	1969	-0.036	-0.192
-0.333		-0.356		-0.333	1970	-0.058	-0.101
-0.641		-0.696		-0.641	1971	-1.015	-1.046
-0.415		-0.539		-0.415	1972	-0.420	-0.482
-0.191		-0.244		-0.191	1973	-0.182	-0.254
-0.611		-0.595		-0.611	1974	-0.804	-0.843
-0.534		-0.560		-0.534	1975	-0.765	-0.800
-0.641		-0.746		-0.641	1976	-0.747	-0.832
-0.233		-0.286		-0.233	1977	-0.214	-0.316
-0.290		-0.343		-0.290	1978	-0.231	-0.291
-0.142		-0.222	-0.244	-0.106	1979	-0.118	-0.174
-0.073	-0.051	-0.086	-0.085	-0.042	1980	0.019	-0.042
-0.127	-0.123	-0.097	-0.127	-0.092	1981	-0.150	-0.221
-0.261	-0.315	-0.312	-0.320	-0.275	1982	-0.214	-0.278
-0.050	-0.108	-0.115	-0.077	-0.061	1983	0.109	0.080
-0.351	-0.382	-0.370	-0.306	-0.335	1984	-0.407	-0.416
-0.357	-0.410	-0.329	-0.396	-0.360	1985	-0.396	-0.420
-0.239	-0.315	-0.263	-0.266	-0.252	1986	-0.222	-0.279

RATPAC	UAH	RSS4.0	ERA-I	ERA5	JRA-55	MERRA-2	Sonde Ave	Sat Avg
0.073					-0.153		-0.037	
-0.316					-0.377		-0.357	
-0.316					-0.415		-0.396	
-0.535					-0.573		-0.593	
-0.458					-0.555		-0.544	
-0.403					-0.479		-0.489	
-0.542					-0.628		-0.625	
-0.711					-0.649		-0.794	
-0.299					-0.377		-0.413	
-0.555					-0.618		-0.634	
-0.462					-0.546		-0.620	
-0.093					-0.064		-0.107	
-0.226					-0.260		-0.128	
-0.833					-0.825		-0.965	
-0.397					-0.300		-0.433	
-0.134					-0.167		-0.190	
-0.693					-0.741		-0.780	
-0.710					-0.717		-0.758	
-0.747					-0.650		-0.775	
-0.263					-0.216		-0.264	
-0.249					-0.271		-0.257	
-0.079	-0.229	-0.114	0.135	-0.008	-0.040		-0.124	-0.171
0.014	-0.098	-0.031	0.086	-0.006	-0.011	-0.026	-0.003	-0.065
-0.099	-0.229	-0.199	-0.091	-0.174	-0.157	-0.189	-0.157	-0.214
-0.195	-0.242	-0.225	-0.114	-0.197	-0.165	-0.254	-0.229	-0.234
0.118	0.159	0.135	0.203	0.144	0.148	0.046	0.102	0.147
-0.364	-0.312	-0.386	-0.340	-0.384	-0.371	-0.440	-0.396	-0.349
-0.383	-0.455	-0.507	-0.384	-0.435	-0.424	-0.522	-0.400	-0.481
-0.278	-0.216	-0.284	-0.204	-0.234	-0.231	-0.371	-0.260	-0.250

0.276	0.309	0.248	0.295	0.277	0.270	0.136	0.246	0.279
0.003	-0.003	-0.061	0.031	0.033	-0.008	0.008	-0.013	-0.032
-0.451	-0.424	-0.443	-0.411	-0.334	-0.396	-0.360	-0.435	-0.433
-0.017	-0.061	-0.102	-0.002	0.057	-0.025	-0.012	-0.027	-0.081
-0.011	0.006	-0.017	0.024	0.062	0.004	0.024	0.019	-0.006
-0.108	-0.177	-0.167	-0.169	-0.090	-0.147	-0.061	-0.130	-0.172
-0.123	-0.115	-0.116	-0.120	-0.046	-0.115	-0.040	-0.128	-0.116
-0.068	-0.037	-0.077	-0.103	-0.047	-0.069	0.003	-0.095	-0.057
0.093	0.135	0.076	0.075	0.110	0.059	0.099	0.075	0.105
-0.171	-0.023	-0.079	-0.115	-0.070	-0.114	-0.066	-0.137	-0.051
-0.072	0.109	0.075	0.042	0.076	0.054	0.126	-0.042	0.092
0.504	0.679	0.588	0.515	0.581	0.581	0.640	0.518	0.633
-0.353	-0.254	-0.282	-0.373	-0.319	-0.269	-0.269	-0.323	-0.268
-0.267	-0.150	-0.187	-0.230	-0.253	-0.192	-0.183	-0.215	-0.168
-0.039	0.025	0.002	-0.028	-0.074	-0.017	0.010	-0.006	0.014
0.197	0.209	0.221	0.148	0.155	0.206	0.245	0.220	0.215
0.249	0.239	0.268	0.217	0.203	0.237	0.299	0.246	0.254
0.206	0.099	0.176	0.116	0.079	0.117	0.212	0.176	0.137
0.377	0.278	0.355	0.318	0.246	0.310	0.382	0.372	0.317
0.238	0.085	0.174	0.182	0.098	0.156	0.155	0.215	0.130
0.188	0.108	0.196	0.125	0.103	0.114	0.118	0.181	0.152
-0.191	-0.254	-0.120	-0.199	-0.191	-0.186	-0.191	-0.178	-0.187
0.219	0.159	0.287	0.207	0.209	0.218	0.148	0.257	0.223
0.524	0.352	0.452	0.381	0.415	0.414	0.305	0.476	0.402
-0.015	-0.142	-0.024	-0.090	-0.080	-0.054	-0.140	-0.062	-0.083
0.087	-0.053	0.078	0.003	0.021	0.045	-0.031	0.098	0.013
0.258	0.099	0.247	0.189	0.200	0.208	0.116	0.268	0.173
0.259	0.146	0.290	0.219	0.237	0.249	0.176	0.296	0.218
0.502	0.353	0.529	0.438	0.472	0.464	0.391	0.512	0.441
0.797	0.628	0.771	0.702	0.724	0.723	0.599	0.792	0.700
0.456	0.333	0.460	0.359	0.447	0.344	0.365	0.466	0.396
0.284	0.141	0.293	0.157	0.278	0.180	0.210	0.277	0.217
0.613	0.473	0.650		0.602	0.492	0.562	0.613	0.561

0.160	0.125	0.175	0.105	0.136	0.136	0.145	0.167	0.150
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MT GL						
		RAOBCOR RICH	RATPAC A UNSW		UAH	
Reanal Avg	1955					
	1956					
	1957					
	1958	-0.162	-0.204	-0.116		
	1959	-0.244	-0.279	-0.203	-0.138	
	1960	-0.255	-0.284	-0.218	-0.214	
	1961	-0.254	-0.291	-0.188	-0.223	
	1962	-0.337	-0.391	-0.322	-0.331	
	1963	-0.209	-0.256	-0.196	-0.257	
	1964	-0.285	-0.325	-0.368	-0.307	
	1965	-0.576	-0.621	-0.523	-0.402	
	1966	-0.306	-0.351	-0.272	-0.247	
	1967	-0.347	-0.382	-0.322	-0.339	
	1968	-0.453	-0.501	-0.397	-0.434	
	1969	-0.201	-0.256	-0.158	-0.195	
	1970	-0.134	-0.149	-0.183	-0.203	
	1971	-0.558	-0.563	-0.476	-0.415	
	1972	-0.454	-0.482	-0.310	-0.343	
	1973	-0.092	-0.138	-0.070	-0.054	
	1974	-0.492	-0.497	-0.421	-0.340	
	1975	-0.407	-0.413	-0.354	-0.237	
	1976	-0.629	-0.657	-0.524	-0.445	
	1977	-0.182	-0.233	-0.066	-0.095	
	1978	-0.215	-0.252	-0.168	-0.175	
0.029	1979	-0.119	-0.149	-0.022	-0.112	-0.110
0.011	1980	0.018	-0.025	0.075	0.022	0.040
-0.153	1981	-0.051	-0.093	0.000	-0.070	-0.051
-0.183	1982	-0.142	-0.167	-0.072	-0.092	-0.128
0.135	1983	0.023	0.011	0.033	0.063	0.069
-0.384	1984	-0.322	-0.344	-0.256	-0.196	-0.250
-0.441	1985	-0.324	-0.357	-0.253	-0.241	-0.299
-0.260	1986	-0.213	-0.254	-0.198	-0.193	-0.209

0.244	1987	0.102	0.061	0.123	0.092	0.093
0.016	1988	0.087	0.084	0.086	0.063	0.066
-0.375	1989	-0.170	-0.142	-0.173	-0.128	-0.188
0.004	1990	0.084	0.119	0.075	0.109	0.029
0.028	1991	0.138	0.164	0.096	0.117	0.095
-0.117	1992	-0.123	-0.119	-0.131	-0.097	-0.119
-0.080	1993	-0.205	-0.212	-0.231	-0.140	-0.197
-0.054	1994	-0.090	-0.118	-0.094	-0.075	-0.080
0.086	1995	-0.050	-0.070	-0.082	-0.065	0.000
-0.091	1996	-0.152	-0.178	-0.197	-0.191	-0.060
0.075	1997	-0.108	-0.146	-0.137	-0.118	-0.022
0.579	1998	0.425	0.410	0.338	0.367	0.425
-0.307	1999	-0.073	-0.077	-0.152	-0.096	-0.080
-0.214	2000	-0.144	-0.153	-0.179	-0.165	-0.103
-0.027	2001	0.051	0.023	0.030	-0.001	0.064
0.189	2002	0.191	0.166	0.181	0.093	0.195
0.239	2003	0.156	0.135	0.178	0.125	0.149
0.131	2004	0.102	0.088	0.095	0.034	0.062
0.314	2005	0.229	0.246	0.242	0.140	0.150
0.148	2006	0.121	0.156	0.167	0.087	0.058
0.115	2007	0.141	0.190	0.143	0.171	0.097
-0.192	2008	-0.143	-0.092	-0.112	-0.084	-0.154
0.195	2009	0.077	0.132	0.111	0.089	0.067
0.379	2010	0.337	0.394	0.373	0.403	0.321
-0.091	2011	-0.005	0.049	0.038	0.085	-0.027
0.009	2012	0.075	0.123	0.108	0.095	0.040
0.178	2013	0.243	0.299	0.255	0.249	0.153
0.220	2014	0.217	0.268	0.234	0.256	0.160
0.441	2015	0.359	0.402	0.394	0.403	0.246
0.687	2016	0.606	0.647	0.576		0.455
0.379	2017	0.432	0.463	0.408		0.317
0.206	2018	0.298	0.335	0.288		0.165
0.552						

0.130	#DIV/0!	0.120	0.143	0.112	0.092	0.090
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							MT Tropics
RSS	ERA5	JRA55	MERRA2	Sonde Ave	Sat Avg	Reanal Avg	
							1955
							1956
							1957
		-0.097		-0.161			1958
		-0.205		-0.216			1959
		-0.283		-0.243			1960
		-0.268		-0.239			1961
		-0.387		-0.345			1962
		-0.283		-0.229			1963
		-0.385		-0.321			1964
		-0.540		-0.530			1965
		-0.292		-0.294			1966
		-0.408		-0.347			1967
		-0.465		-0.446			1968
		-0.169		-0.202			1969
		-0.242		-0.167			1970
		-0.521		-0.503			1971
		-0.368		-0.397			1972
		-0.125		-0.089			1973
		-0.523		-0.438			1974
		-0.407		-0.353			1975
		-0.564		-0.564			1976
		-0.167		-0.144			1977
		-0.216		-0.202			1978
-0.172	0.017	-0.093		-0.100	-0.141	-0.038	1979
-0.008	0.078	0.023	-0.004	0.022	0.016	0.032	1980
-0.101	-0.023	-0.074	-0.117	-0.054	-0.076	-0.071	1981
-0.174	-0.093	-0.151	-0.207	-0.118	-0.151	-0.151	1982
0.029	0.081	0.012	-0.038	0.033	0.049	0.018	1983
-0.300	-0.271	-0.299	-0.379	-0.279	-0.275	-0.316	1984
-0.345	-0.327	-0.321	-0.425	-0.294	-0.322	-0.357	1985
-0.270	-0.180	-0.199	-0.304	-0.214	-0.240	-0.228	1986

0.030	0.152	0.079	0.020	0.094	0.062	0.084	1987
-0.001	0.131	0.077	0.068	0.080	0.032	0.092	1988
-0.260	-0.122	-0.177	-0.209	-0.154	-0.224	-0.169	1989
-0.033	0.143	0.057	0.055	0.097	-0.002	0.085	1990
0.042	0.198	0.083	0.048	0.129	0.068	0.110	1991
-0.146	-0.014	-0.127	-0.111	-0.118	-0.133	-0.084	1992
-0.222	-0.147	-0.194	-0.158	-0.197	-0.210	-0.167	1993
-0.097	-0.088	-0.074	-0.066	-0.094	-0.088	-0.076	1994
-0.024	-0.050	-0.008	-0.011	-0.067	-0.012	-0.023	1995
-0.075	-0.148	-0.094	-0.116	-0.179	-0.068	-0.119	1996
-0.029	-0.103	-0.058	-0.037	-0.127	-0.026	-0.066	1997
0.430	0.352	0.395	0.443	0.385	0.428	0.396	1998
-0.044	-0.165	-0.100	-0.107	-0.100	-0.062	-0.124	1999
-0.060	-0.272	-0.126	-0.119	-0.160	-0.081	-0.172	2000
0.124	-0.086	0.033	0.081	0.026	0.094	0.009	2001
0.269	0.148	0.190	0.220	0.158	0.232	0.186	2002
0.226	0.097	0.159	0.245	0.148	0.188	0.167	2003
0.128	0.054	0.090	0.184	0.080	0.095	0.109	2004
0.218	0.124	0.219	0.286	0.214	0.184	0.210	2005
0.125	0.089	0.129	0.176	0.133	0.091	0.131	2006
0.156	0.140	0.129	0.178	0.161	0.127	0.149	2007
-0.090	-0.130	-0.112	-0.071	-0.108	-0.122	-0.104	2008
0.124	0.118	0.094	0.121	0.102	0.095	0.111	2009
0.370	0.395	0.366	0.351	0.377	0.345	0.371	2010
0.030	0.002	0.020	0.005	0.042	0.001	0.009	2011
0.099	0.064	0.084	0.046	0.100	0.070	0.065	2012
0.220	0.228	0.208	0.183	0.262	0.187	0.206	2013
0.234	0.245	0.222	0.222	0.244	0.197	0.230	2014
0.328	0.363	0.328	0.361	0.389	0.287	0.351	2015
0.541	0.589	0.562	0.520	0.610	0.498	0.557	2016
0.400	0.448	0.389	0.398	0.434	0.359	0.412	2017
0.244	0.288	0.234	0.263	0.307	0.204	0.262	2018
							2019
0.135	0.099	0.116	0.140	0.123	0.112	0.116	

RAOB AVC	RAOBCOR	RICH	RATPAC A	UNSW	UAH	RSS	NOAA	UW
-0.262	-0.202	0.093	0.107					
-0.289	-0.220	-0.069	-0.216	-0.310				
-0.276	-0.214	-0.209	-0.259	-0.383				
-0.391	-0.349	-0.332	-0.368	-0.366				
-0.436	-0.387	-0.389	-0.349	-0.415				
-0.294	-0.240	-0.227	-0.320	-0.298				
-0.421	-0.369	-0.356	-0.319	-0.367				
-0.700	-0.653	-0.648	-0.560	-0.402				
-0.338	-0.297	-0.290	-0.143	-0.207				
-0.506	-0.477	-0.456	-0.354	-0.400				
-0.576	-0.518	-0.532	-0.394	-0.466				
0.003	0.059	0.061	-0.010	-0.120				
0.130	0.123	0.113	-0.106	-0.069				
-0.943	-0.951	-0.953	-0.714	-0.472				
-0.451	-0.432	-0.437	-0.296	-0.310				
-0.135	-0.103	-0.111	-0.035	0.025				
-0.729	-0.721	-0.729	-0.580	-0.419				
-0.677	-0.671	-0.684	-0.545	-0.333				
-0.707	-0.673	-0.680	-0.578	-0.368				
-0.260	-0.211	-0.225	-0.152	-0.156				
-0.191	-0.159	-0.148	-0.147	-0.102				
-0.121	-0.097	-0.085	0.028	-0.090	-0.079	-0.155	-0.209	-0.171
0.033	0.068	0.077	0.112	0.078	0.033	-0.034	-0.107	-0.045
-0.139	-0.102	-0.132	-0.033	-0.119	-0.125	-0.187	-0.227	-0.191
-0.107	-0.083	-0.082	0.026	-0.069	-0.100	-0.163	-0.208	-0.174
0.234	0.242	0.245	0.303	0.249	0.278	0.229	0.186	0.210
-0.461	-0.457	-0.473	-0.408	-0.219	-0.378	-0.451	-0.507	-0.473
-0.405	-0.396	-0.394	-0.360	-0.250	-0.406	-0.470	-0.511	-0.469
-0.259	-0.241	-0.247	-0.239	-0.202	-0.251	-0.321	-0.359	-0.311

0.298	0.317	0.303	0.349	0.207	0.313	0.247	0.226	0.274
0.004	0.008	0.013	0.054	0.062	0.012	-0.061	-0.086	-0.038
-0.363	-0.375	-0.374	-0.359	-0.166	-0.383	-0.458	-0.497	-0.443
0.096	0.088	0.087	0.115	0.151	0.002	-0.059	-0.089	-0.040
0.131	0.139	0.141	0.101	0.100	0.072	0.020	-0.012	0.031
0.006	0.029	0.000	-0.031	0.017	-0.061	-0.091	-0.126	-0.090
-0.076	-0.049	-0.057	-0.114	-0.023	-0.083	-0.110	-0.144	-0.106
-0.106	-0.067	-0.086	-0.106	-0.097	-0.067	-0.091	-0.119	-0.087
0.057	0.084	0.088	0.042	0.060	0.106	0.088	0.072	0.106
-0.184	-0.148	-0.146	-0.266	-0.208	-0.102	-0.116	-0.139	-0.097
-0.027	0.027	0.036	-0.113	-0.064	0.090	0.090	0.074	0.106
0.554	0.577	0.575	0.499	0.423	0.644	0.656	0.660	0.686
-0.270	-0.263	-0.265	-0.320	-0.258	-0.231	-0.193	-0.217	-0.206
-0.237	-0.235	-0.230	-0.297	-0.232	-0.198	-0.153	-0.173	-0.161
-0.043	-0.034	-0.033	-0.063	-0.132	-0.011	0.051	0.037	0.041
0.123	0.134	0.138	0.149	0.032	0.137	0.226	0.229	0.217
0.170	0.180	0.180	0.230	0.121	0.179	0.268	0.285	0.248
0.098	0.103	0.109	0.145	0.038	0.065	0.144	0.199	0.137
0.268	0.240	0.241	0.311	0.100	0.190	0.269	0.362	0.267
0.192	0.147	0.159	0.205	0.063	0.077	0.143	0.240	0.139
0.083	0.033	0.049	0.115	0.083	0.047	0.113	0.203	0.092
-0.243	-0.293	-0.293	-0.281	-0.149	-0.262	-0.199	-0.110	-0.215
0.150	0.093	0.101	0.131	0.070	0.103	0.170	0.256	0.153
0.412	0.351	0.359	0.486	0.410	0.348	0.409	0.507	0.392
-0.095	-0.154	-0.142	-0.047	0.095	-0.110	-0.051	0.043	-0.072
-0.037	-0.086	-0.084	-0.057	-0.002	-0.106	-0.020	0.046	-0.051
0.206	0.150	0.168	0.175	0.278	0.102	0.188	0.246	0.147
0.232	0.186	0.198	0.189	0.279	0.123	0.210	0.258	0.163
0.510	0.470	0.475	0.479	0.488	0.375	0.463	0.507	0.402
0.675	0.637	0.656	0.692		0.550	0.645	0.717	0.604
0.383	0.351	0.381	0.370		0.270	0.364	0.439	0.325
0.222	0.181	0.218	0.233		0.102	0.199	0.289	0.174
0.496	0.490	0.502	0.547		0.385	0.484	0.543	0.466

0.124	0.104	0.110	0.106	0.074	0.089	0.141	0.182	0.131
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ERA-I	ERA5	JRA55	MERRA2	Sonde Avg	Sat Avg	Reanal Avg
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		-0.029		-0.124		
		-0.254		-0.193		
		-0.343		-0.233		
		-0.426		-0.357		
		-0.466		-0.404		
		-0.361		-0.253		
		-0.477		-0.382		
		-0.597		-0.667		
		-0.279		-0.308		
		-0.518		-0.480		
		-0.499		-0.542		
		0.005		0.041		
		-0.196		0.122		
		-0.788		-0.949		
		-0.296		-0.440		
		-0.103		-0.116		
		-0.695		-0.726		
		-0.661		-0.677		
		-0.597		-0.686		
		-0.187		-0.232		
		-0.195		-0.166		
0.082	0.016	-0.016		-0.101	-0.154	0.000
0.093	0.056	0.051	-0.007	0.059	-0.038	0.033
-0.086	-0.118	-0.116	-0.159	-0.124	-0.183	-0.131
-0.081	-0.113	-0.106	-0.181	-0.091	-0.161	-0.133
0.239	0.251	0.215	0.111	0.240	0.225	0.192
-0.376	-0.436	-0.418	-0.499	-0.463	-0.453	-0.451
-0.390	-0.430	-0.417	-0.544	-0.398	-0.464	-0.464
-0.228	-0.237	-0.235	-0.391	-0.249	-0.310	-0.288

0.289	0.325	0.296	0.149	0.306	0.265	0.257
0.044	0.079	0.020	0.029	0.008	-0.044	0.043
-0.366	-0.317	-0.373	-0.338	-0.371	-0.445	-0.343
0.047	0.124	0.043	0.048	0.090	-0.047	0.072
0.080	0.145	0.077	0.086	0.137	0.028	0.103
-0.099	0.009	-0.059	0.015	0.012	-0.092	-0.012
-0.106	-0.035	-0.079	-0.014	-0.061	-0.111	-0.042
-0.115	-0.075	-0.059	-0.012	-0.086	-0.091	-0.049
0.061	0.100	0.092	0.120	0.076	0.093	0.104
-0.160	-0.153	-0.132	-0.091	-0.159	-0.113	-0.125
0.026	0.043	0.064	0.129	0.012	0.090	0.079
0.529	0.603	0.622	0.675	0.569	0.661	0.633
-0.316	-0.293	-0.259	-0.249	-0.266	-0.212	-0.267
-0.246	-0.340	-0.222	-0.215	-0.234	-0.171	-0.259
-0.043	-0.149	-0.056	-0.022	-0.037	0.029	-0.076
0.118	0.072	0.144	0.183	0.132	0.202	0.133
0.182	0.129	0.186	0.251	0.177	0.245	0.189
0.093	0.030	0.087	0.170	0.103	0.136	0.096
0.263	0.161	0.255	0.313	0.250	0.272	0.243
0.176	0.100	0.129	0.146	0.166	0.150	0.125
0.114	0.095	0.053	0.087	0.055	0.114	0.078
-0.197	-0.197	-0.256	-0.224	-0.276	-0.197	-0.226
0.162	0.172	0.122	0.107	0.115	0.170	0.134
0.386	0.455	0.381	0.321	0.374	0.414	0.386
-0.064	-0.039	-0.084	-0.120	-0.130	-0.048	-0.081
-0.043	-0.055	-0.064	-0.098	-0.069	-0.033	-0.072
0.185	0.203	0.155	0.102	0.175	0.171	0.154
0.213	0.228	0.186	0.148	0.205	0.188	0.188
0.474	0.496	0.436	0.390	0.485	0.437	0.441
0.675	0.673	0.657	0.569	0.656	0.629	0.633
0.467	0.410	0.350	0.317	0.372	0.350	0.359
0.343	0.237	0.189	0.170	0.207	0.191	0.199
	0.542	0.483	0.499	0.496	0.469	0.508
0.110	0.113	0.109	0.125	0.113	0.136	0.113
						#DIV/0!

300-200 Tropics

	RAOBCOR	RICH	RATPAC A	ERA-I	ERA5	JRA55	MERRA2
1955							
1956							
1957							
1958	0.208	-0.06917	-0.112				
1959	-0.057	-0.2125	-0.596				
1960	-0.185	-0.25417	-0.509				
1961	-0.530	-0.55917	-0.682				
1962	-0.463	-0.47125	-0.519				
1963	-0.371	-0.38083	-0.632				
1964	-0.603	-0.56208	-0.622				
1965	-0.964	-0.93417	-0.792				
1966	-0.448	-0.42042	-0.216				
1967	-0.773	-0.71958	-0.579				
1968	-0.765	-0.7925	-0.662				
1969	0.042	-0.00167	-0.106				
1970	0.148	0.314583	-0.192				
1971	-1.394	-1.19333	-1.106				
1972	-0.566	-0.5175	-0.392				
1973	-0.118	-0.05	-0.139				
1974	-0.971	-0.81292	-0.846				
1975	-1.013	-0.83583	-0.812				
1976	-0.974	-0.99042	-0.812				
1977	-0.198	-0.28375	-0.149				
1978	-0.146	-0.20125	-0.229				
1979	-0.055	-0.08708	0.081	0.137	0.111		
1980	0.087	0.03	0.121	0.09	0.068		
1981	-0.227	-0.31917	-0.139	-0.207	-0.225		
1982	-0.240	-0.34625	-0.099	-0.32	-0.281		
1983	0.269	0.2275	0.244	0.188	0.268		
1984	-0.715	-0.74667	-0.722	-0.705	-0.709		
1985	-0.595	-0.64	-0.626	-0.727	-0.695		
1986	-0.207	-0.23292	-0.286	-0.376	-0.291		

1987	0.533	0.500417	0.581	0.472	0.545
1988	0.040	0.051667	0.104	0.069	0.122
1989	-0.592	-0.53375	-0.406	-0.547	-0.515
1990	0.092	0.120417	0.218	0.047	0.11
1991	0.170	0.11125	0.164	0.117	0.17
1992	-0.087	-0.15708	-0.146	-0.172	-0.08
1993	-0.099	-0.17458	-0.219	-0.208	-0.111
1994	-0.031	-0.13125	-0.159	-0.15	-0.08
1995	0.125	0.101667	0.028	0.11	0.132
1996	-0.150	-0.17958	-0.406	-0.18	-0.185
1997	0.154	0.057917	-0.059	0.146	0.162
1998	0.906	0.97375	0.741	0.934	0.964
1999	-0.459	-0.34542	-0.486	-0.376	-0.473
2000	-0.323	-0.19958	-0.426	-0.289	-0.495
2001	-0.056	0.037083	-0.106	0.022	-0.222
2002	0.307	0.350417	0.278	0.263	0.197
2003	0.328	0.3775	0.374	0.311	0.242
2004	0.185	0.239167	0.234	0.195	0.126
2005	0.432	0.54375	0.531	0.486	0.374
2006	0.186	0.37	0.278	0.327	0.202
2007	0.065	0.262917	0.188	0.201	0.198
2008	-0.579	-0.37208	-0.512	-0.376	-0.326
2009	0.138	0.319583	0.194	0.234	0.281
2010	0.389	0.555	0.641	0.622	0.669
2011	-0.328	-0.17917	-0.166	-0.111	-0.073
2012	-0.167	-0.01542	-0.119	-0.078	-0.052
2013	0.176	0.329583	0.214	0.289	0.31
2014	0.300	0.43375	0.281	0.352	0.387
2015	0.628	0.73375	0.644	0.707	0.71
2016	0.995	1.095833	1.051	1.057	1.046
2017	0.496	0.605417	0.538	0.447	0.548
2018	0.275	0.4075	0.307667	0.151	0.325
2019	0.752	0.881667	0.837667		

10.000	0.151	0.216	0.164	0.171	0.168	#DIV/0!	#DIV/0!
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		300-150 Tropics		
Sonde Ave	Reanalyses	RAOBCORE	RICH	RATPAC A
		1955		
		1956		
		1957		
0.009		1958	0.336875	0.02625
-0.288		1959	0.0715625	-0.13625
-0.316		1960	-0.0813542	-0.2227083
-0.590		1961	-0.4471875	-0.505625
-0.484		1962	-0.37	-0.4173958
-0.461		1963	-0.3263542	-0.3891667
-0.596		1964	-0.5069792	-0.5215625
-0.897		1965	-0.8857292	-0.89625
-0.361		1966	-0.4047917	-0.4096875
-0.691		1967	-0.6953125	-0.6667708
-0.740		1968	-0.7072917	-0.7489583
-0.022		1969	0.01802083	-0.0364583
0.090		1970	0.221875	0.3009375
-1.231		1971	-1.2984375	-1.1929167
-0.492		1972	-0.5988542	-0.6325
-0.102		1973	-0.1235417	-0.1077083
-0.877		1974	-0.8926042	-0.7869792
-0.887		1975	-0.9366667	-0.8064583
-0.926		1976	-0.9136458	-0.9090625
-0.210		1977	-0.2307292	-0.2928125
-0.192		1978	-0.1497917	-0.1957292
-0.020	0.124	1979	-0.0586458	-0.0792708
0.079	0.079	1980	0.048125	0.00645833
-0.228	-0.216	1981	-0.22125	-0.294375
-0.229	-0.3005	1982	-0.2248958	-0.3065625
0.247	0.228	1983	0.26604167	0.23729167
-0.728	-0.707	1984	-0.7134375	-0.731875
-0.620	-0.711	1985	-0.5903125	-0.6447917
-0.242	-0.3335	1986	-0.19625	-0.2384375

0.538	0.5085	1987	0.50739583	0.4578125
0.065	0.0955	1988	0.05302083	0.05666667
-0.511	-0.531	1989	-0.5178125	-0.4369792
0.143	0.0785	1990	0.12770833	0.1978125
0.149	0.1435	1991	0.20104167	0.18885417
-0.130	-0.126	1992	-0.05	-0.0815625
-0.164	-0.1595	1993	-0.0991667	-0.1584375
-0.107	-0.115	1994	-0.0135417	-0.1034375
0.085	0.121	1995	0.13770833	0.08479167
-0.245	-0.1825	1996	-0.1130208	-0.1892708
0.051	0.154	1997	0.19822917	0.06885417
0.874	0.949	1998	0.89947917	0.91385417
-0.430	-0.4245	1999	-0.4115625	-0.3505208
-0.316	-0.392	2000	-0.306875	-0.2221875
-0.041	-0.1	2001	-0.0627083	0.01552083
0.312	0.23	2002	0.25770833	0.3028125
0.360	0.2765	2003	0.24895833	0.30645833
0.220	0.1605	2004	0.13760417	0.20125
0.502	0.43	2005	0.3728125	0.49614583
0.278	0.2645	2006	0.09510417	0.29145833
0.172	0.1995	2007	-0.0069792	0.20552083
-0.488	-0.351	2008	-0.6084375	-0.3832292
0.217	0.2575	2009	0.04802083	0.24947917
0.528	0.6455	2010	0.33083333	0.51229167
-0.224	-0.092	2011	-0.3404167	-0.1714583
-0.101	-0.065	2012	-0.2344792	-0.0519792
0.240	0.2995	2013	0.0928125	0.26677083
0.338	0.3695	2014	0.2065625	0.3653125
0.669	0.7085	2015	0.51354167	0.6459375
1.047	1.0515	2016	0.86322917	0.98875
0.546	0.4975	2017	0.371875	0.5028125
0.330	0.238	2018	0.18583333	0.33020833
0.824		2019	0.61114583	0.751875

0.177	0.170	10.000	0.116	0.184	#DIV/0!
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ERA-I	ERA5	JRA55	MERRA2	Sonde Ave	Reanalyses
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				0.182	
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				-0.032	
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				-0.152	
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				-0.476	
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				-0.394	
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				-0.358	
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				-0.514	
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				-0.891	
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				-0.407	
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				-0.681	
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				-0.728	
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				-0.009	
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				0.261	
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				-1.246	
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				-0.616	
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				-0.116	
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				-0.840	
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				-0.872	
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				-0.911	
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				-0.262	
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				-0.173	
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	0.015			-0.069	0.015
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	0.027			0.027	0.027
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	-0.212			-0.258	-0.212
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	-0.293			-0.266	-0.293
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	0.237			0.252	0.237
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	-0.716			-0.723	-0.716
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	-0.661			-0.618	-0.661
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	-0.273			-0.217	-0.273
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0.495	0.483	0.495
0.124	0.055	0.124
-0.493	-0.477	-0.493
0.104	0.163	0.104
0.183	0.195	0.183
-0.061	-0.066	-0.061
-0.119	-0.129	-0.119
-0.086	-0.058	-0.086
0.118	0.111	0.118
-0.193	-0.151	-0.193
0.151	0.134	0.151
0.912	0.907	0.912
-0.429	-0.381	-0.429
-0.49	-0.265	-0.49
-0.21	-0.024	-0.21
0.177	0.280	0.177
0.206	0.278	0.206
0.113	0.169	0.113
0.347	0.434	0.347
0.178	0.193	0.178
0.225	0.099	0.225
-0.283	-0.496	-0.283
0.288	0.149	0.288
0.682	0.422	0.682
-0.024	-0.256	-0.024
-0.031	-0.143	-0.031
0.315	0.180	0.315
0.375	0.286	0.375
0.698	0.580	0.698
1	0.926	1
0.514	0.437	0.514
0.312	0.258	0.312
	0.682	

#DIV/0!	0.172	#DIV/0!	#DIV/0!	0.150	0.172
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250-100

	RAOBCORE RICH	RATPAC A	ERA-I	ERA5	JRA55	MERRA2
1955						
1956						
1957						
1958	0.614	0.334				
1959	0.432	0.159				
1960	0.111	-0.122				
1961	0.002	-0.137				
1962	-0.087	-0.222				
1963	0.033	-0.129				
1964	-0.010	-0.138				
1965	-0.449	-0.538				
1966	-0.169	-0.261				
1967	-0.319	-0.344				
1968	-0.472	-0.527				
1969	0.050	-0.018				
1970	0.417	0.337				
1971	-0.922	-0.995				
1972	-0.599	-0.768				
1973	-0.024	-0.142				
1974	-0.637	-0.683				
1975	-0.644	-0.660				
1976	-0.639	-0.592				
1977	-0.271	-0.257				
1978	-0.161	-0.164				
1979	-0.083	-0.049		-0.077		
1980	-0.053	-0.055		-0.005		
1981	-0.172	-0.197		-0.082		
1982	-0.029	-0.060		-0.099		
1983	0.391	0.378		0.394		
1984	-0.583	-0.586		-0.541		
1985	-0.511	-0.564		-0.504		
1986	-0.253	-0.291		-0.221		

1987	0.382	0.324			0.359
1988	0.078	0.056			0.187
1989	-0.306	-0.198			-0.365
1990	0.207	0.336			0.131
1991	0.295	0.354			0.262
1992	0.093	0.112			0.052
1993	0.066	0.029			0.021
1994	0.029	-0.046			-0.091
1995	0.150	0.025			0.099
1996	-0.132	-0.267			-0.279
1997	0.202	0.078			0.016
1998	0.802	0.736			0.694
1999	-0.220	-0.261			-0.212
2000	-0.298	-0.299			-0.456
2001	-0.179	-0.134			-0.332
2002	-0.020	0.037			-0.048
2003	0.049	0.115			0.034
2004	-0.029	0.041			-0.048
2005	0.127	0.236			0.139
2006	-0.034	0.126			0.072
2007	-0.152	0.010			0.193
2008	-0.520	-0.368			-0.171
2009	-0.131	-0.002			0.221
2010	0.227	0.345			0.578
2011	-0.221	-0.100			0.106
2012	-0.386	-0.219			-0.107
2013	-0.073	0.100			0.197
2014	-0.033	0.124			0.290
2015	0.279	0.425			0.550
2016	0.432	0.566			0.692
2017	0.111	0.246			0.398
2018	0.000	0.124			0.221
2019	0.338	0.457			

10.000	0.029	0.081	#DIV/0!	#DIV/0!	0.110	#DIV/0!	#DIV/0!
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		RAOBCOF RICH			RATPAC / ERA-I		ERA5	
		TTT						
Sonde Ave	Reanalyses	RAOBCOF RICH			RATPAC / UAH		RSSv4.0	
		1955						
		1956						
		1957						
0.474		1958	0.038	-0.101	0.024			
0.295		1959	-0.200	-0.245	-0.385			
-0.005		1960	-0.276	-0.286	-0.369			
-0.067		1961	-0.482	-0.591	-0.560			
-0.154		1962	-0.466	-0.503	-0.459			
-0.048		1963	-0.391	-0.413	-0.507			
-0.074		1964	-0.536	-0.594	-0.540			
-0.494		1965	-0.788	-0.966	-0.719			
-0.215		1966	-0.398	-0.452	-0.286			
-0.331		1967	-0.605	-0.752	-0.532			
-0.500		1968	-0.629	-0.825	-0.520			
0.016		1969	0.017	-0.034	-0.111			
0.377		1970	0.047	0.283	-0.199			
-0.959		1971	-1.090	-1.225	-0.915			
-0.684		1972	-0.459	-0.550	-0.380			
-0.083		1973	-0.137	-0.082	-0.124			
-0.660		1974	-0.815	-0.845	-0.695			
-0.652		1975	-0.796	-0.868	-0.702			
-0.615		1976	-0.782	-1.022	-0.722			
-0.264		1977	-0.212	-0.316	-0.202			
-0.163		1978	-0.188	-0.233	-0.238			
-0.066	-0.077	1979	-0.093	-0.119	-0.029	-0.104	-0.169	
-0.054	-0.005	1980	0.045	-0.002	0.023	-0.013	-0.075	
-0.184	-0.082	1981	-0.171	-0.351	-0.099	-0.172	-0.232	
-0.044	-0.099	1982	-0.202	-0.378	-0.170	-0.218	-0.281	
0.385	0.394	1983	0.180	0.195	0.200	0.207	0.160	
-0.585	-0.541	1984	-0.507	-0.779	-0.456	-0.408	-0.480	
-0.538	-0.504	1985	-0.453	-0.672	-0.461	-0.475	-0.539	
-0.272	-0.221	1986	-0.231	-0.265	-0.267	-0.252	-0.320	

0.353	0.359	1987	0.328	0.468	0.347	0.348	0.281
0.067	0.187	1988	0.017	0.020	0.048	0.015	-0.060
-0.252	-0.365	1989	-0.452	-0.566	-0.449	-0.464	-0.541
0.271	0.131	1990	0.026	0.088	0.023	-0.062	-0.125
0.325	0.262	1991	0.086	0.079	0.032	0.025	-0.031
0.103	0.052	1992	-0.116	-0.189	-0.132	-0.177	-0.211
0.047	0.021	1993	-0.096	-0.207	-0.132	-0.127	-0.150
-0.008	-0.091	1994	-0.061	-0.163	-0.071	-0.041	-0.062
0.088	0.099	1995	0.099	0.070	0.080	0.125	0.108
-0.199	-0.279	1996	-0.119	-0.212	-0.216	-0.050	-0.065
0.140	0.016	1997	0.040	0.026	-0.086	0.114	0.116
0.769	0.694	1998	0.657	0.942	0.578	0.748	0.757
-0.240	-0.212	1999	-0.334	-0.377	-0.400	-0.297	-0.257
-0.298	-0.456	2000	-0.222	-0.232	-0.306	-0.197	-0.148
-0.157	-0.332	2001	-0.009	0.005	-0.075	-0.002	0.066
0.008	-0.048	2002	0.231	0.318	0.205	0.208	0.302
0.082	0.034	2003	0.257	0.345	0.280	0.245	0.338
0.006	-0.048	2004	0.153	0.207	0.187	0.102	0.185
0.182	0.139	2005	0.357	0.512	0.422	0.303	0.379
0.046	0.072	2006	0.170	0.338	0.223	0.089	0.157
-0.071	0.193	2007	0.114	0.231	0.200	0.115	0.175
-0.444	-0.171	2008	-0.327	-0.404	-0.294	-0.288	-0.224
-0.067	0.221	2009	0.177	0.288	0.222	0.176	0.239
0.286	0.578	2010	0.412	0.523	0.564	0.411	0.465
-0.160	0.106	2011	-0.172	-0.211	-0.036	-0.125	-0.068
-0.303	-0.107	2012	-0.026	-0.047	0.020	-0.043	0.044
0.013	0.197	2013	0.197	0.298	0.222	0.137	0.221
0.046	0.290	2014	0.268	0.402	0.281	0.187	0.269
0.352	0.550	2015	0.517	0.702	0.538	0.407	0.498
0.499	0.692	2016	0.812	1.064	0.866	0.702	0.793
0.178	0.398	2017	0.465	0.573	0.477	0.352	0.438
0.062	0.221	2018	0.275	0.375	0.299	0.169	0.261
0.398		2019	0.624	0.850	0.684	0.511	0.617

0.055	0.110		0.147	0.216	0.160	0.128	0.179
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0.98587	1	0.97852	0.97511	0.93924
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JRA55 MERRA2 Sonde Av Reanalyses

NOAA UW ERA5 JRA55 MERRA2 Sonde Av Sat Avg Reanalyses Avg

			-0.092		-0.013		
			-0.395		-0.277		
			-0.424		-0.310		
			-0.598		-0.544		
			-0.558		-0.476		
			-0.509		-0.437		
			-0.670		-0.557		
			-0.718		-0.824		
			-0.388		-0.379		
			-0.672		-0.629		
			-0.590		-0.658		
			-0.052		-0.043		
			-0.231		0.043		
			-0.918		-1.077		
			-0.317		-0.463		
			-0.143		-0.114		
			-0.767		-0.785		
			-0.764		-0.789		
			-0.690		-0.842		
			-0.182		-0.243		
			-0.243		-0.220		
-0.245	-0.204	-0.009	-0.018		-0.080	-0.186	-0.013
-0.171	-0.103	-0.006	0.014	-0.043	0.022	-0.089	-0.011
-0.285	-0.245	-0.180	-0.160	-0.201	-0.207	-0.238	-0.180
-0.338	-0.300	-0.238	-0.212	-0.295	-0.250	-0.291	-0.248
0.102	0.128	0.175	0.146	0.033	0.192	0.144	0.118
-0.556	-0.517	-0.483	-0.445	-0.531	-0.581	-0.499	-0.487
-0.589	-0.542	-0.512	-0.476	-0.612	-0.529	-0.541	-0.534
-0.367	-0.313	-0.255	-0.231	-0.408	-0.254	-0.316	-0.298

0.255	0.308	0.333	0.332	0.169	0.381	0.294	0.278
-0.096	-0.043	0.067	0.017	0.033	0.028	-0.052	0.039
-0.588	-0.529	-0.395	-0.452	-0.407	-0.489	-0.535	-0.418
-0.161	-0.107	0.061	-0.024	-0.014	0.046	-0.116	0.007
-0.067	-0.019	0.091	0.025	0.039	0.066	-0.025	0.051
-0.247	-0.207	-0.097	-0.168	-0.083	-0.146	-0.209	-0.116
-0.185	-0.142	-0.063	-0.122	-0.040	-0.145	-0.146	-0.075
-0.087	-0.051	-0.048	-0.034	0.033	-0.098	-0.056	-0.016
0.095	0.133	0.122	0.091	0.145	0.083	0.116	0.119
-0.089	-0.041	-0.103	-0.106	-0.037	-0.182	-0.058	-0.082
0.100	0.136	0.077	0.076	0.166	-0.007	0.115	0.107
0.765	0.793	0.703	0.711	0.778	0.726	0.761	0.731
-0.281	-0.269	-0.354	-0.319	-0.315	-0.371	-0.275	-0.329
-0.170	-0.156	-0.311	-0.215	-0.210	-0.253	-0.163	-0.245
0.052	0.056	-0.114	-0.030	-0.004	-0.026	0.054	-0.049
0.306	0.295	0.162	0.226	0.260	0.251	0.298	0.216
0.357	0.317	0.209	0.261	0.323	0.294	0.328	0.265
0.246	0.179	0.082	0.130	0.209	0.182	0.182	0.140
0.480	0.376	0.279	0.366	0.419	0.430	0.377	0.355
0.268	0.156	0.121	0.145	0.153	0.243	0.157	0.139
0.280	0.158	0.153	0.114	0.142	0.181	0.167	0.136
-0.116	-0.232	-0.228	-0.283	-0.262	-0.342	-0.228	-0.258
0.339	0.226	0.237	0.194	0.157	0.229	0.233	0.196
0.577	0.451	0.510	0.443	0.360	0.500	0.458	0.438
0.040	-0.086	-0.054	-0.100	-0.159	-0.140	-0.077	-0.104
0.121	0.015	0.000	-0.003	-0.057	-0.018	0.029	-0.020
0.288	0.180	0.231	0.189	0.113	0.239	0.200	0.178
0.324	0.221	0.287	0.249	0.187	0.317	0.245	0.241
0.552	0.437	0.533	0.474	0.405	0.586	0.468	0.470
0.874	0.751	0.817	0.819	0.694	0.914	0.772	0.777
0.522	0.398	0.488	0.438	0.374	0.505	0.418	0.433
0.359	0.232	0.297	0.264	0.215	0.316	0.246	0.258
0.650	0.568	0.659	0.612	0.601	0.719	0.592	0.624

0.226	0.170	0.154	0.147	0.157	0.174	0.174	0.150
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Comment or Suggested Edit

helpful if these undertainties were made more explicit, listed in a concluding section, and prioritized in some way - what are the top 10 priority research areas? If the opening remarks by Secretary Wright and the title pointed to uncertainties and the need for more research, I believe this report will be better received. As I read the report and left review comments below, **I bolded items where I gather the**

This would be more correct: "Some scenarios of future CO2 emissions overestimate observed levels"

This would be more correct: Some detailed climate models run "hot" in their simulation of the climate of the past few decades, while many have underestimated the amount of surface warming. **More research is needed to**

Need reference for: "Claims of increased frequency or intensity of hurricanes, tornadoes, floods, and droughts are not supported by historical data." **More research is needed to identify how frequency and intensity of**

It is misleading to separate the photo-chemical effects of CO2 from the temperature effects. Extreme heat is hard on plants, causing them to lose water, close stomata, etc. It depends on the plant and the degree of heat. **More**

Again it is misleading to separate the CO2 and the temperature effects on the oceans. The warming surface waters is having significant impact on ocean fish and habitats due to the overall increase in global temperatures

More accurate to say "because their effect remain largely unknown". Good examples include natural aerosols (sea salt, dust, biogenic aerosols). Are there others to mention? **More research is needed to understand**

What scenarios are the models using in this figure?

Vegetation is only one way that CO2 is accommodated by land processes, the other is through soils and microbial processes Microbial dynamics is complex and challenging to understand but may also be a way to boost CO2

absorption by soils (which also enriches the soil nutrients!). **More research is needed to better understand how**

More research is needed to improve the understanding and representation of land systems, carbon and

Carbon uptake by oceans and ocean ecosystems is less well studies and modeled. The lack of spread of carbon in ocean models may result from insufficient information, ocean biogeochemistry, ecosystems and model

development. **More research is needed to study and model carbon, nutrient and ecosystem processes and**

More research is needed to map warming trends in urban, non-urban and other environments and to ensure accurate representation of regional and global trends in temperature.

"This practice" - need to clarify whether this refers to "emergent property" or discarding. I believe the authors

"assumed positive cloud feedback" - this is an emergent property too, based on simulation/observation. Should

be rephrased to not use the word "assumed". **Further research is needed to better understand and model how**

Further research is needed to narrow the uncertainty on climate sensitivity, both using models and

The text and figure refer to 33 models, which would include the best and worst. How much does the

How many models are included in each case?

How are the lower and mid-troposphere defined?

"excess amplification" - amplification of what? And Figure 5.6 shows tropics, is this bias only tropical?

Further research is needed to improve how models represent clouds and dynamics; additional observations

Further research is needed to improve how models represent planetary albedo to align with observations.

The greater concern with hurricanes is the amount of moisture the carry and drop after landfall, i.e. flooding.

While this is an active area of research, it is worth noting that this may be the bigger issue for hurricane change

The concern for many are the extreme hot temperatures without night-time cooling that provides an opportunity for recovery. This section doesn't address this. In this regards, the focus on the difference between extreme hot

and extreme cold is misleading when generalizing about decrease in extremes (figure 6.3.4) - the decrease is

Combining heat and humidity as a measure of extreme heat is not unusual since it is this combination that is most impactful to human health - the body cannot cool if the humidity and heat are both high. Since a warmer atmosphere holds more moisture, and CO2 causes heat (and therefore moisture) to increase, this combination is a relevant assessment of the effects of CO2 on extreme conditions that make it difficult for people. Also

Patterns and variability of precipitation are poorly understood and models are particularly challenged to represent and predict precipitation, further research in this area is needed

The authors rightly describe the extreme uncertainty regarding sea level rise. It would be helpful to add some information about the complex, highly nonlinear and uncertain processes involved with ice-sheet dynamics and ice-sheet - ocean interactions that are especially key for Antarctica. **More research is needed to study and model**

Further research is needed on climate variability, effects of ocean circulation, solar variability, model

Anthropogenic aerosol effects may also influence the inflections in temperature in ways that are challenging to Reductions in aerosol indirect (cloud brightening) effects may also explain the reduced planetary albedo, not just from ships but from reduced fossil fuel aerosols coming from the continents, China and east asia especially. This paper describes the reduction in aerosols <https://www.nature.com/articles/s41612-023-00488-y> **This is another** What are the numbers in the 3rd column? Please include in the caption.

I don't see an inconsistency between what Ch 11 and Ch 8 say. The first is about precipitation, droughts, tropical cyclones, heat - overall. The 2nd (ch 8) is about specific types of events in specific regions. Suggest to soften the

The science of attribution of extreme events is challenging and computationally expensive; this is an area where further research is needed with potential to use AI to improve statistics

This section seems to gloss over many key points. Certainly there are limits where extreme heat and drought (water is key) could be detrimental to crops. It also depends on which crops. There is extensive literature on how certain crop viability is shifting. So a region with particular crop experience and cultivation may no longer be able to sustain that agriculture. There is cost to shifting crops across regions and farmers that needs to be accounted Severe weather continues to disproportionately impact lower income communities as well as business that requires outdoor exposure. A thorough analysis would need to include these points and I recommend adding this Related to my previous comment, deaths due to extreme heat conditions appear to be increasing, particularly for certain populations and for those with underlying health conditions (which can be hard to detangle when An additional concern is if the grid fails under either extreme heat demands or cold/severe-storm events, the impact on communities will not be uniform and depends on grid infrastructure which can be better in more The impacts of sea level rise and coastal inundation on coastal communities and in low-lying countries should be addressed. This will have impacts particularly on certain countries/regions but also on world economics

Research is needed to better understand the likelihood and impacts of various tipping points, including changes to ocean circulation patterns, ice sheet acceleration, sea-ice loss, die-off of tropical forests, thawing of

Do the authors think it worthwhile for private or public research, such as at DOE, to seek breakthrough technology that might effectively remove massive amounts of CO2 from the atmosphere?

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Comment or Suggested Edit

The greening effect can't be due to increase in CO₂ alone. The fertilization effect needs Nitrogen and phosphorous. There is observational[1] evidence that nitrogen available to plants is decreasing with increasing CO₂ and thus acting to limit fertilization effect. Secondly, the greening of some portions of the planet are likely due to changes in precipitation patterns associated with changing climatic conditions and not entirely attributable to fertilization effect. We will also need to consider that the temperature effect on photosynthesis will also be a limiting mechanism to any continued greening due to fertilization in the future [2]. I recommend acknowledging that the greening is not attributable to CO₂ alone and continued greening in the future with increasing CO₂ is uncertain.

I am glad we acknowledge that CO₂ causes warming, though I am not sure why we are not considering other energy sector related emissions that also cause warming (CFCs/HFCs, methane, aerosol effects). It is not clear what is meant by "CO₂ emissions have tended to overestimate observed trends". This is not correct, the cumulative emissions track the RCP8.5 scenario the closest [3,4]. While there was a decrease in emissions during the Covid-19 period the emissions are now back on track following RCP8.5. This statement should clarify what is meant by the statement in the text.

This paragraph seems to be talking about equilibrium climate sensitivity. The most recent model inter-comparison gives a wider range of climate sensitivities in the range of 1.8 to 5.7 and is wider than estimates of climate sensitivities that have been estimated from paleoclimatic and more recent historical datasets, in the range could be in the range of 2.3 to 4.5 K[5]. The higher sensitivity in the most recent model assessments are an area of active investigation by modelers, the feasibility of a higher range needs to be confirmed with additional observational and process scale modeling [6]. The range for climate sensitivities, 1.8-2.7, should be corrected to the most recent findings, 2.3-4.5. We should also recognize that the (a)earth is a complex system of systems (b)we can't do an experiment to find out what is correct or reduced the uncertainty. As we get better at extracting temperature records and CO₂ concentrations from paleo data, there will be better reconstructions and possibly narrower range along with improvements in modeling that resolve many physical, biological and chemical processes as we get to higher and cloud resolving spatial resolutions.

This is again not true for the majority of the models in the AR6. Figure 7.19 in the IPCC AR6 report shows that majority of the models exhibit a range within the observational range. The models running hot in the most recent decades are the ones with climate sensitivities greater than 5K, which are 3 out of a total of 40 and it should be noted that about the same number of models also are running cold' compared to observed[7]

There is very little dispute that these are challenging issues for climate science. Many of the issues identified here related to compound effects (subsidence and sea-level rise; wildfire and forest management) that requires further scientific investigation. Identifying further research avenues/focus areas will be helpful to firm up some of the challenges faced in using the climate projections as discussed in the paragraph 9.

The focus on uncertainty is relevant and should be emphasized in future research. However, as a reasonable policy pathways, making decisions in the face of these uncertainties is critical. Most of the climate uncertainties that we have confidence at this time can be considered Level 2 and Level 3 uncertainties, approaches such as scenario analysis (and others) are suggested and followed for making hazard and risk estimates for future conditions. For deep uncertainty hazards (for example tornadoes etc.) that we don't have enough data or capability to model, developing methods for assessing the uncertainty and risk should be a focus of future research.

The reason CO₂ was identified as a pollutant is the health consequences of increased temperature, flooding and other climate impacts and not because of any direct affect on health due to exposure to atmospheric CO₂[8]. The summary should note that CO₂ fertilization effects are limited by the availability of other critical plant nutrients (Nitrogen, Phosphorous). The fertilization effect is also constrained by higher temperature effecting photosynthesis[9]

The attribution of greening to primarily CO₂ fertilization is questionable as per recent research. Specifically, in the Northern high latitudes (where the greening is most prominent), increases in temperatures due to climate change has been shown to provide the best explanation[10]. In the sub-Saharan region reforestation efforts and changing precipitation patterns lead to some of the observed greening (the great green wall) [11]. The attribution to CO₂ fertilization should be qualified by noting the other present and emerging constraints.

This summarization ignores the compound effects of temperature, moisture and CO₂ fertilization in assessing the impacts of CO₂ increase on vegetation and crop yields. Many studies have shown that [12]. Making note of these compensating factors is required for a balanced view on CO₂ fertilization effects on plants. Chen et al. (2024)[13] conclude that "In the attribution analysis of LAI trend and growth rate trend, there were some differences between multiple linear regression model and partial correlation analysis at high latitudes in the northern hemisphere. Partial correlation analysis showed that LAI trend and growth rate trend in this region were mainly affected by temperature and radiation, while multiple linear regression suggested that CO₂ was the dominant driver. The results of the partial correlation analysis seem more reasonable because some previous studies have shown that vegetation change in the high latitudes of the northern Hemisphere is mainly positively affected by climate warming. Multiple linear regression model performed relatively poorly in this region and might not fully identify the contribution of individual drivers. In addition, our model does not include the contribution of land management, which has been highlighted in some previous studies. Of course, the contribution of land management to LAI trend and growth rate trend may be implied in other drivers, such as the positive contribution of CO₂ to LAI trend in PP and PN areas".

This again suffers from not acknowledging the effects of compound and often compensating phenomena that is occurring with the on-going climate change. For example [14] note that much of the Midwest any benefit from CO₂ fertilization will be negated by temperature increases. [15] note that "Our results show that long-term physiological acclimation dampens the initial stimulation of plant net carbon assimilation to elevated [CO₂], and of plant water use to warming."

The fallacy of these arguments in terms of PH changes and evolution is that the changes described in this paragraph occurred over millennia and the evolutionary process had time to adapt; here with climate change we are talking about changes in our lifetime, the speed of change is the issue. This will lead to collapse of some ecosystem and by the time adaptation takes place it will be millions of years and in a different climate - not the one we have now and that enabled the rise of humans.

A simple calculation will show us how misleading this figure is. It shows that over 600 Million years CO₂ changed by around 6000ppm. That is a rate of change of 0.00001/yr; CO₂ changed from 275 to 430 in the past 175 years, that is rate of change of 0.88ppm/yr. A change in the rate of over 10⁵ in magnitude - there in lies the problem. We are seeing a rapid increase in CO₂ that has never been witnessed and the ecosystem and huma society (which is at best 10K years old), may not be able to adapt to this rapid change.

The misuse of RCP8.5 as business as usual is acknowledged. However, this was never intended to be a no-policy or business as usual scenario but as a high-end baseline scenario. When dealing with interaction of physical systems with socio-economic projections (which tend to be highly uncertain and policy dependent), the development of this high baseline scenarios is intended to explore the uncertainty ranges that represent a high-end scenario[16,17]. As any engineer would acknowledge, this is a prudent approach when dealing with L3 and L4 type deep uncertainties and provide valid envelopes for assessing uncertainties and risks from high impact events/hazards. The rest of the statements here are uncertainties acknowledged by the climate scientists and included in developing projections and discussing the results[4]. Does the IPCC downplay the role of sun in climate change? The IPCC includes sun variability in all its assessments from the beginning and has been acknowledged as a potential but insignificant contributor.

Please see above. The business-as-usual may be a misnomer but this is an 95% case that is typically included in any type of prudent uncertainty analysis, in particular given the difficulty of predicting the evolution of socio-economic and political conditions over the next 100 years. It should be noted the difference between RCP8.5 and RCP4.5 for mid-century conditions that is of particular focus for adaptation studies in not significant and most of the divergence in these two scenarios occurs later in the century.

That the dynamic vegetation models need more development is acknowledged and is a defining challenge for Earth System Modeling for the next decade.

As noted, Parker[18,19,20] has investigated the Urban effects on temperature records. The finding establish that by comparing warm and wind conditions world wide that the impact is negligible. However, as noted by authors, this literature hasn't progressed much over the last decade and much more attention needs to be paid to this question by employing newer models, datasets and analytical techniques available to us at present.

We can all agree that there is a desperate need for developing higher-resolution climate models that can get to cloud resolving scale so that we can represent the cloud feedbacks correctly in the model and avoid uncertainties from parameterization and scale dependency of the parameters. This doesn't make these models useless. The models provide directions for further improvements and necessary changes to reduce the uncertainty bands over the ECS.

The databased approaches have mostly been robust with changes at the high end around 3-4C and at the low end around 1.8 to 2.5C as noted in the chapter. It will be challenging to make this range shorter given the data requirements and uncertainties in data over paleo/haloocene periods. It seems reasonable to estimate that we may have ECS in the range of 3 to 4K (higher than 3.5K being less likely [21]) at the higher end and this should not prevent us from planning and thinking on ways to prevent this possible scenario as it could have major consequences for humans across the planet.

The models range over a factor of three in ECS comparing the most sensitive to the least sensitive models. However vast majority of the models are in 3 to 3.5K sensitivity range and it is probably not correct to assign all models the same amount of importance, given the fact that some of institutes participating in the exercise have different levels of capacity to develop and test models.

While this analysis for the CMIP6 model set is accurate and focuses on a dataset that has shown higher ECS than previous iterations, it should be noted the models have exhibited considerable skill in predicting the subsequent GMST warming[22]. The criticism of the CMIP6 based high ECS models may be premature and probably will have to wait additional time before passing judgement. As noted in [22] these models have shown considerable skill when evaluated on their projections over the past 30-40 years after the projections were published.

A recent study attributes the bias to inter-annual availability and residual bias in the satellite record. The pre- and post 2000 have temperature records from two separate satellites and the discrepancy in the trends needs to be resolved[23]

This is challenge we need to face and work on improving the parametrizations. The new era of super high resolution models would resolve the complex interactions of turbulence, transport and clouds and will provide less uncertainty[24]. However, this can't be used to invalidate the entire set of models, the models are performing remarkably well given the complex system that is being modeled. It should be noted the models do cover the range of the observations and it is not outside the envelope of model predictions.

Part of the problem here may be which part of the stratosphere is sampled and the importance of interannual variabilities in the lower part of the stratosphere. [25] have shown that including the stratosphere as defined from 25 to 50km there is high confidence that the cooling signal caused by CO2 increase is detectable and beyond the noise levels of the natural and inter annual variability in the lowest part of the stratosphere. We should put this debate to rest.

Given the large uncertainties in obtaining data over much of the Northern Hemisphere, using a smaller regional analysis to discount the models may be inappropriate. We should that this remains a question we need to resolve developing better datasets with more seasonal and sub-seasonal coverage to test the model on a global scale

This statement from [26] refers to the fitness of global scale models to resolve regional scale features and argues for developing model at higher spatial resolutions. Using downscaling and other techniques additional insights can be gained at regional scales and provide information for a set of 'purposes'. However, we should work on getting to regional and local scales with GCM as quickly as possible.

Looking for trends or estimating trends in extreme events in current and future climate is not necessarily an attribution study. Estimating frequency, duration and intensity of events helps understand the changing range of the hazard (if there is one). An attribution would be to find to what extent a particular event is influenced or affected by increase in CO2. I would consider these two not to be the same.

Attributing any single event to changing climate is perilous, agreed.

As noted by [26] there is not yet any strong evidence that LPT is a fact
I am not sure how one can conclude that the temperature extremes have decreased based on figure 6.3.4. If I understand correctly the Tmax-Tmin for each year was tabulated and a mean of this difference averaged over the 100+ years was subtracted from these values to get some thing like a anomaly. This anomaly seems to have moved from +3F to -3F over the course of 100 years and now trending upwards again. This suggests to me that there has been significant changes in the extremes over the years and the most recent trend is towards warmer highs?

The NCA5 is suggesting that the western US is experiencing increase in extreme heat (page 57, para 4); it seems like figure 6.3.5 establishes the fact and not contradict. There was no claim of pervasive (all CONUS) increase in the report

The definition of heat wave as consecutive 6 days seems to be a special case. The standard definition is exceedance of 85 or 90 percentile for 2 or more days. I can't check with NCA5 as it was taken down from the web

Figure 6.3.6 establishes that heatwaves as defined here have increased in the west and have shown increasing trend all over CONUS in the past 50 years. [27] shows the results for the last 60 years and there is little doubt that there is an increase over most of the CONUS, again the NCA5 report is off the web; figure 6.3.7 shows the heat waves are monotonically increasing from the 1960. Including the longer data is only interesting in the dust bowl 1930 camouflage the signal somewhat for the Midwest and central plains. The problem of taking averages over large regions (for example entire CONUS) is that it kills the peak signals and smooths out the emergent climate change indicators. Doing continental averages to look for extremes is really not very useful. Secondly, there is no particular reason to assume that the climate change signal (i.e. the number of heat waves) should showing up 100 years ago, as the CO2 in the atmosphere started to be of significance in the last 50 years.

averaged over all stations in the region, none of these trend parameters is statistically significant'. This is again how one would be looking at statistics of extremes in precipitation. As we know, precipitation is highly heterogenous and location dependent. As observed there are trends even with the approaches chosen by the authors of this study compared to NCA5 and averaging that over and saying there is no trend seems disingenuous.

same argument as above

again the issue here is that we are talking about events that are happening in a short-time and over a small region. Averaging over time and space and develop statistics is probably not appropriate when we are talking about events such as the recent flooding event in Texas. If you average that event over 30 days, it will seem unremarkable.

As noted in NCA5 and shown in the analysis presented in figure 6.4.4 there is a clear trend of increase in extreme precipitation in 12 of the 27 stations analyzed. Again averaging over the entire region is not the best method for picking extreme precipitation events that are local both in time and space.

However, there is evidence that flash droughts, which last weeks have increased over the Northeast and Midwest [28]

More recent analysis indicate forest loss due to wildfire accelerating over the recent past[29]. In particular there has been an increase in extreme fire radiative power with a 2 fold increase from 2003 to 2023 (period of satellite data availability)[30][31]. However, that these fires are not out-of-sample and there is a fire deficit as shown in figure 6.8.2 should be acknowledged. But this doesn't alleviate the concern that wildfire is leading to lot of socio-economic concerns and needs to be addressed[32]

The question of forest management and its role on wildfire frequency and intensity is interesting and deserves further study.

The global mean sea-level was increasing at a rate of 0.08 inches/yr in 1993 compared 0.18 inches/yr in 2023, almost double the rate[33], which is approximately what is needed to meet the NOAA projections by mid-century and seems plausible.

A possible reason the method used by IPCC (optimal fingerprinting) can be considered to address McKitnick criticism is in [34]

The role of clouds remains the single most uncertainty in climate modeling, I am glad this was acknowledged here.

The substance of this paragraph was addressed in my comments in earlier sections. Some of the claims made here are either exaggerations of the usual practice (RCP8.5 being referred to as BAU) or the comment about not fit for purpose (a comment extracted from a publication that is calling out for cloud resolved models.

The problem with both the FACE studies and the soybean, Maize and wheat studies cited here are that they don't consider the effect of increase in temperature, changes in precipitation, humidity and other environmental factors along with CO2 increases. These compound effects have been shown in wide number of studies [35][36][37][38][39]. A meta analysis of the compound effects shows that increase in CO2, along with temperature, precipitation changes effects the quality of the cereal and yields[40]. Another recent study evaluated the impacts on C3 and C4 crops and conclude that CO2 enrichment for C3 crops could increase but will be compensated by temperature increase. CO2 fertilization effect was found to be small for C4 [41]. It is important therefore that we consider the compound effects on crop yields and not just focus on CO2 enrichment.

Taylor and Schlenker 2021 also note that 'Climate change will likely have negative impact on agriculture in aggregate, especially in regions exposed to extreme heat. And the CO2-driven yield increases may be offset by effects on food nutrition and quality'. However, the results for US have been a net positive in the recent past but not true in the lower latitudes.

The criticism of NOAA Billion dollar map is likely warranted as it was never completely transparent how the data was generated. However, changing the baseline assumption and refactoring the data using a different set of criteria to make the effects smaller also doesn't make sense. We should continue collecting this data and make the data accessible for researchers and peer review. Figure 10.1 doesn't address these issues, it is another methodology with unknown province of the data.

Climate change can be expected to increase cold weather extremes in regions that have not been exposed to these effect

The same Nobel prize winning model in its most recent study concludes that [42] "We conclude with three results relevant for climate policy. First, both current policies (base run) and the extended Paris Accord fall short of limiting global warming to 2 °C or to the cost–benefit optimal level. Second, the economic stakes in global climate policy are substantial, with estimated net present value of economic benefits around \$120 trillion from the cost–benefit optimal policy. Third, once differences in discounting are considered, the baseline DICE-2023 estimate of the social cost of carbon (\$66/tCO₂ for 2020) aligns closely with other recent estimates". Obviously this is the latest and the current version of the model and these results are quite different from thus discussed on this page. These conclusions should also be included in this discussion to avoid selective reading of the literature.

Similar empirical studies [43] point to "Using an empirical approach that provides a robust lower bound on the persistence of impacts on economic growth, we find that the world economy is committed to an income reduction of 19% within the next 26 years independent of future emission choices (relative to a baseline without climate impacts, likely range of 11–29% accounting for physical climate and empirical uncertainty). These damages already outweigh the mitigation costs required to limit global warming to 2 °C by sixfold over this near-term time frame and thereafter diverge strongly dependent on emission choices. Committed damages arise predominantly through changes in average temperature, but accounting for further climatic components raises estimates by approximately 50% and leads to stronger regional heterogeneity. Committed losses are projected for all regions except those at very high latitudes, at which reductions in temperature variability bring benefits. The largest losses are committed at lower latitudes in regions with lower cumulative historical emissions and lower present-day income". This study uses more of the daily temperature precipitation from 1600 hundred locations world wide instead of global means. There are numerous studies that show the cost, many described in the COP 21 and follow-on meetings

while small in terms of global emissions (just from the US transport sector), over period this will be significant reduction. We need to remember that US is the second highest emitter of CO₂.

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Impacts of Carbon Dioxide Emissions on the U.S. Climate

Climate Working Group
United States Department of Energy
May 27, 2025

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Impacts of Carbon Dioxide Emissions on the U.S. Climate

Report to U.S. Energy Secretary Christopher Wright

May 27, 2025

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SECRETARY'S FOREWORD

Energy, Integrity, and the Power of Human Potential

Over my lifetime, I've had the privilege of working as an energy entrepreneur across a range of fields—nuclear, geothermal, natural gas, and more—and I now serve as Secretary of Energy under President Donald Trump. But above all, I'm a physical scientist who sees modern energy as nothing short of miraculous. It powers every aspect of modern life, drives every industry, and has made America an energy powerhouse with the ability to fuel global progress.

The rise of human flourishing over the past two centuries is a story worth celebrating. Yet we are told—relentlessly—that the very energy systems that enabled this progress now pose an existential threat. Hydrocarbon-based fuels, the argument goes, must be rapidly abandoned or else we risk planetary ruin.

That view demands scrutiny. That's why I commissioned this report: to encourage a more thoughtful and science-based conversation about climate change and energy. With my technical background, I've reviewed reports from the Intergovernmental Panel on Climate Change, the U.S. government's assessments, and the academic literature. I've also engaged with many climate scientists, including the authors of this report.

What I've found is that media coverage often distorts the science. Many people—even well-meaning ones—walk away with a view of climate change that is exaggerated or incomplete. To provide clarity, I asked a diverse team of independent experts to summarize the current state of climate science, with a focus on how it relates to the United States.

I didn't select these authors because we always agree—far from it. In fact, they may not always agree with each other. But I chose them for their rigor, honesty, and willingness to elevate the debate. I exerted no control over their conclusions. What you'll read are their words, drawn from the best available data and scientific assessments.

I've reviewed the report carefully and challenged its findings. I believe it faithfully represents the state of climate science today. Still, many readers may be surprised by its conclusions—which differ in important ways from the mainstream narrative. That's a sign of how far the public conversation has drifted from the science itself.

To correct course, we need open, respectful, and informed debate. That's why I'm inviting public comment on this report. Honest scrutiny and scientific transparency should be at the heart of our policymaking.

Climate change is real, and it deserves attention. But it is not the greatest threat facing humanity. That distinction belongs to global energy poverty. As someone who values data, I know that improving the human condition depends on expanding access to reliable, affordable energy. Climate change is a challenge—not a catastrophe. But misguided policies based on fear rather than facts could truly endanger human well-being.

We stand at the threshold of a new era of energy leadership. If we empower innovation rather than restrain it, America can lead the world in providing cleaner, more abundant energy—lifting billions out of poverty, strengthening our economy, and improving our environment along the way.

EXECUTIVE SUMMARY

This report reviews scientific certainties and uncertainties in how anthropogenic carbon dioxide (CO₂) emissions have affected, or will affect, the Nation's climate, extreme weather events, and selected metrics of societal well-being. Those emissions are increasing the concentration of CO₂ in the atmosphere through a complex and variable carbon cycle, where some portion of the additional CO₂ persists in the atmosphere for centuries.

Elevated concentrations of CO₂ directly enhance plant growth, globally “greening” the planet and increasing agricultural productivity. They also make the oceans less alkaline (lower the pH) by an amount within the range of natural variability. That is possibly detrimental to coral reefs, although the recent rebound of the Great Barrier Reef suggests otherwise.

Carbon dioxide also acts as a greenhouse gas, exerting a warming influence on climate and weather. Scenarios of future CO₂ emissions have tended to overestimate observed levels.

The world's several dozen detailed climate models offer little guidance on how the climate responds to elevated CO₂, with the average surface warming under a doubling of the CO₂ concentration ranging from 1.8°C to 5.7°C, a larger range than simpler, data driven estimates, which suggest a response in the range 1.8°C to 2.7°C.

Detailed climate models generally run “hot” in their description of the climate of the past few decades - too much warming at the surface and too much amplification of warming in the lower- and mid-troposphere. They also produce too much stratospheric cooling, too much snow loss, and too much warming in the US Corn Belt. The combination of overly sensitive models and extreme scenarios for future emissions has exaggerated projections of future warming.

Most extreme weather events do not show long-term trends. Claims of increased frequency or intensity of hurricanes, tornadoes, floods, and droughts are not supported by historical data. Additionally, forest management practices are often overlooked in assessing wildfire activity. Global sea level has risen approximately 8 inches since 1900, but there are significant regional variations in tide gauge data driven primarily by local land subsidence; U.S. tide gauge measurements in aggregate show no obvious acceleration in sea level rise beyond the historical average rate.

The attribution of particular climate changes or extreme weather events to human CO₂ emissions is challenged by natural climate variability, data limitations, and inherent model deficiencies. Moreover, solar activity's contribution to the warming climate late 20th century warming might be underestimated.

Both models and experience suggest that CO₂-induced warming might be less damaging economically than commonly believed, and excessively aggressive mitigation policies could prove more detrimental than beneficial. Social Cost of Carbon estimates, which attempt to quantify the economic damage of CO₂ emissions, are highly sensitive to their underlying assumptions and so provide limited independent information.

The report supports a more nuanced and evidence-based approach for informing climate policy. The risks and benefits of a climate changing under both natural and human influences must be weighed against the costs, efficacy, and collateral impacts of any “climate action”, considering the nation's need for reliable and affordable energy with minimal local pollution. THIS IS POLICY AND WE DON'T REALLY DISCUSS THIS. AS DISCUSSED IN EMAILS, WE SHOULD KEEP IT IN. Beyond continuing precise, un-interrupted observations of the global climate system, it will be important to make realistic assumptions about future emissions, re-evaluate climate models to address biases and uncertainties, and clearly acknowledge the limitations of extreme event attribution studies. An approach that acknowledges both the

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potential risks and benefits of CO₂, rather than relying on flawed models and extreme scenarios, is essential for informed and effective decision-making.

PREFACE

This document originated in late March 2025 when Secretary Wright assembled an independent group to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the U.S. public. We agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The group began working in early April with a deadline of May 28. The short timeline and the technical nature of the material meant that we could not comprehensively review all topics. While the report is intended to be accessible to non-experts, we have omitted some introductory or explanatory material that can easily be accessed elsewhere. Nor have we attempted to survey entire literatures related to the topics covered. We have focused as much as possible on literature published since 2020 and referenced previous IPCC and NCA assessment reports. We have also used data through 2024 where possible.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support of independent scientific assessment and open scientific debate.

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**PART I: DIRECT HUMAN INFLUENCE ON ECOSYSTEMS AND THE
CLIMATE**

1 CARBON DIOXIDE AS A POLLUTANT

Chapter summary:

Carbon dioxide (CO₂) differs in many ways from the so-called Criteria Air Pollutants. It does not affect local air quality and has no human toxicological implications at ambient levels. It is an issue of concern because of its potential effects on the global climate, a complex issue that occupies much of this report.

The Clean Air Act of 1970 defined six so-called Criteria Air Contaminants subject to regulation (EPA): particulate matter, ground-level ozone, sulfur dioxide, nitrogen dioxide, lead, and carbon monoxide. In 2007, the Supreme Court ruled that greenhouse gases (CO₂ among them) were also “pollutants” subject to regulation under Clean Air Act (*Mass. v. EPA*, 2007). While the definition of “pollutant” is ultimately a legal ~~matter~~, there are important scientific distinctions between CO₂ and the Criteria Air Contaminants. The latter are subject to regulatory control because they cause local problems depending on concentrations that include nuisances (odor, visibility), damage to plants, and, at high enough exposure levels, toxicological effects in humans. In contrast, CO₂ is odorless, does not affect visibility and has no toxicological effects at ambient levels. It is a naturally occurring part of the atmosphere and a key component of human and plant respiration. CO₂ is essential for plant photosynthesis and higher levels are beneficial for vegetation. In these aspects, CO₂ is similar to water vapor.

Ambient outdoor air today contains about 430 parts per million (ppm) CO₂, increasing at about 2 ppm per year. The U.S. Occupational Safety and Health Administration issues guidelines for indoor workplaces in which elevated CO₂ might be encountered, such as where dry ice is used. The Permissible Exposure Limit is 5,000 ppm over 8 hours (OSHA, 2024). Allen *et al.* (2015) reported evidence of diminished performance on some cognitive tasks among workers in office cubicles when exposed to CO₂ levels above 1,000-1,500 ppm. These levels are far larger than any plausible ambient outdoor value through the end of the 22nd century.

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The growing amount of CO₂ in the atmosphere directly influences the earth system by promoting plant growth (global greening), thereby enhancing agricultural yields, and by neutralizing ocean alkalinity. But the primary concern about CO₂ is its role as a greenhouse gas (GHG) that alters the earth's energy balance. How the climate will respond to that influence is a complex question that will occupy much of this report.

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2 DIRECT IMPACTS OF CO₂ ON THE ENVIRONMENT

Chapter summary:

CO₂ enhances photosynthesis and improves plant water use efficiency, thereby promoting plant growth. Global greening due to increased CO₂ levels in the atmosphere is well-established on all continents.

CO₂ absorption in sea water makes the oceans less alkaline. The recent decline in pH is within the range of natural variability on millennial time scales. Most ocean life evolved when the oceans were mildly acidic. Decreasing pH might adversely affect corals, although the Australian Great Barrier Reef has shown considerable growth in recent years.

2.1 CO₂ and global greening

The growing CO₂ concentration in the atmosphere has the important positive effect of promoting plant growth by enhancing photosynthesis and improving water use efficiency. That is evident in the “global greening” phenomenon discussed below, as well as in the improving agricultural yields discussed in Chapter 10.

2.1.1 Measurement of global greening

“Greening” refers to an increase in the fraction of the Earth’s surface covered by plants. It can be quantified by the “Leaf Area Index” (LAI) measured by satellite. Many studies over the past decade have confirmed a global greening pattern (increase in LAI) attributable to rising CO₂ levels. Zhu *et al.* (2016) was one of the first studies to report that global greening was detectable using satellite sensors. From 1982 to 2011 they detected greening over 25-50 percent of the Earth versus “browning” over only 4 percent and attributed 70 percent of the greening to rising CO₂ levels (see Figure 2.1).

Zheng (2017) confirmed the pattern, noting that greening over thirty years had added 8 percent to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen *et al.* (2019) noted that China and India were exploiting it through land management changes. Thus, while China accounts for only 6.6 percent of global vegetated area it accounts for 25 percent of global net increase in LAI. Piao *et al.* (2020) noted that greening was even observable in the Arctic.

While plant models predict increased photosynthesis in response to rising CO₂, Haverd *et al.* (2020) reported a CO₂ fertilization rate nearly double model predictions. That is, CO₂ fertilization had driven an increase in observed global photosynthesis by 30 percent since 1900, versus 17 percent predicted by plant models. This indicates that global models of the socioeconomic impacts of rising CO₂ have likely understated the benefits to crops and agriculture. The connection between CO₂ fertilization and agriculture will be discussed in Chapter 9.

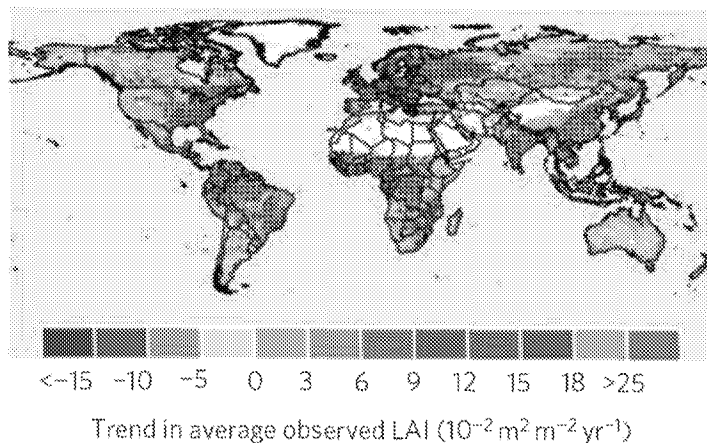


Figure 2.1: Trends in average Leaf Area Index (LAI). Source: Zhu *et al.* 2016 Figure 3.

Finally, Chen *et al.* (2024) surveyed claims that greening had slowed since 2000 due to drought stress. They found instead that faulty satellite sensors were the cause and that the corrected data showed accelerated greening over 55 percent of the globe while browning was accelerating over only 7 percent. In other words, the greening trend continued with no evidence of slowdown, and CO₂ fertilization remained the dominant driver.

2.1.2 Photosynthesis and CO₂ levels

Plants build biomass through *photosynthesis*, a process that converts carbon dioxide, water, and light into sugar. The plant enzyme responsible for photosynthesis is Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the Rubisco enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass. This is referred to as the “C3” process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually many times higher than they are today, as shown in Figure 2.2.

About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd *et al.* 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining, falling to as low as 170 ppm during glaciations (Gerhart and Ward 2010).

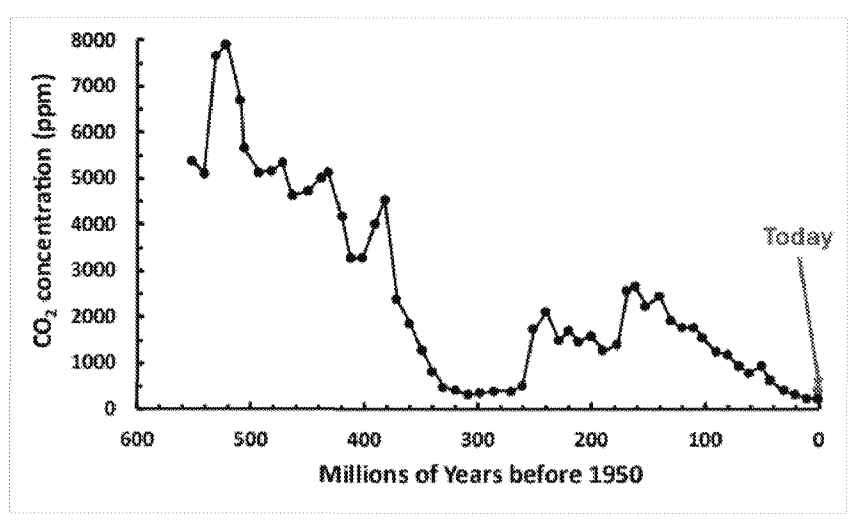


Figure 2.2. Ambient CO₂ levels over the past 550 million years. Today's concentration of 430 ppm is also shown. Source: (Berner 2006)

In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C₄, in which CO₂ is concentrated in the vicinity of Rubisco, allowing for the C₃ process to function more efficiently. For agricultural purposes the plant categories are:

- C₃: rice, wheat, soybeans and most other crops
- C₄: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth would have declined and eventually ceased. Below 180 ppm, the growth rates of many C₃ species are reduced 40-60 percent relative to 350 ppm (Gerhart and Ward 2010) and growth has stopped altogether under experimental conditions of 60-140 ppm CO₂. Some C₄ plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Current CO₂ levels are about 430 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 2.3, reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains induced by increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

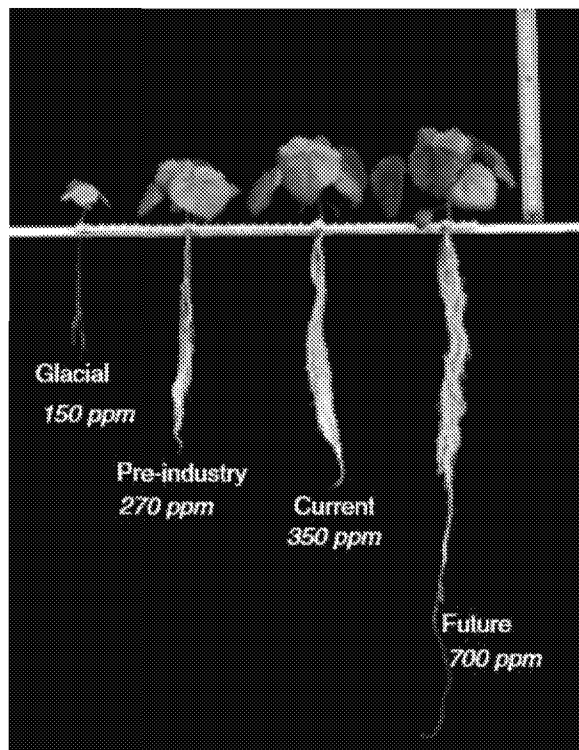


Figure 2.3: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010). Note “Current” corresponds to 1988 in image.

Over the past 60+ years there have been thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, allowing water to evaporate. Under enriched CO₂ conditions the stomata remain closed for longer periods, thus helping the plant retain water longer, and so increasing water use efficiency.

Specific effects of climate change on U.S. agriculture will be reviewed in Chapter 9.

2.1.3 Rising CO₂ and crop water use efficiency

Derying *et al.* (2016) surveyed evidence on crop water productivity (CWP), the yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and to reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data (Free Air CO₂

Enrichment—see Chapter 9) on crop yield changes for maize (corn), wheat, rice, and soybean and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 emissions scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. They reported that models without CO₂ fertilization predicted CWP losses in every region, but those were more than offset by CO₂ fertilization so that all regions showed a net CWP gain. Deryng *et al.* (2016) also reported that negative impacts of warming on wheat and soybean yields were fully offset by CWP gains and mitigated by up to 90 percent for rice and 60 percent for maize.

Similarly, Cheng *et al.* (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that global water use by plants had not increased, despite the extra biomass.

Deryng *et al.* (2016) assumed that climate change would “exacerbate water scarcity”. Yet while models do predict that drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang *et al.* (2024) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; at most only 4 percent of currently arid areas will see increased desertification.

2.1.4 CO₂ fertilization benefits in IPCC Reports

The IPCC has only minimally discussed global greening and CO₂ fertilization of agricultural crops. The topic is briefly acknowledged in a few places in the body of the IPCC 6th and earlier Assessment Reports but is omitted in all Summary documents. Section 2.3.4.3.3 of the AR6 Working Group I report, entitled “global greening and browning,” points out that the IPCC Special Report on Climate Change and Land had concluded with *high confidence* that greening had increased globally over the past 2-3 decades. It then discusses that there are variations in the greening trend among data sets, concluding that while they have *high confidence* greening has occurred, they have *low confidence* in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports.

Overall, however, the Policymaker Summaries, Technical Summaries, and Synthesis Reports do not discuss the topic.

2.2 The Alkaline Oceans

2.2.1 Changing pH

A neutral aqueous solution has a pH of 7.0, while one with pH greater than 7.0 is alkaline (also termed basic) and with pH less than 7.0 is acidic. The modern-day global average pH of sea water is estimated to be 8.04 (Copernicus Marine Service 2025), down from an estimated value of 8.2 in pre-Industrial times (Gattuso and Hansson, 2011). As CO₂ concentrations in the atmosphere increased, the oceans absorbed more, which decreases their pH. Depending upon the oceans’ buffering capacity, they are expected to become somewhat less alkaline over time, consistent with the observed decrease in pH.

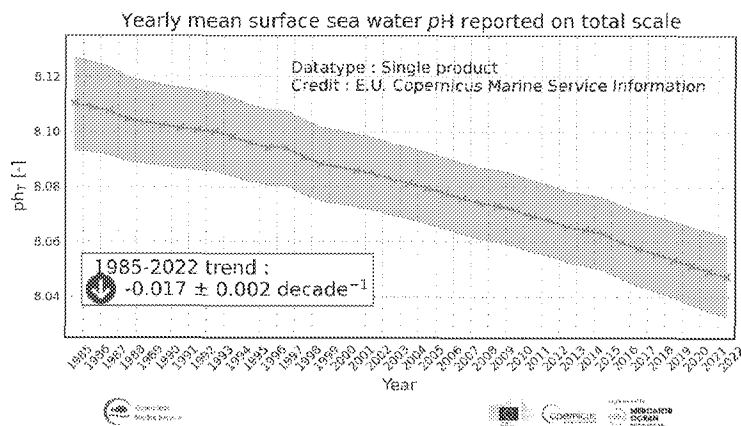


Figure 2.4: Ocean pH 1985 – 2022. Source: Copernicus Marine Service 2025

While this process is often called “ocean acidification”, it is a misnomer because the oceans are not expected to become acidic; “ocean neutralization” would be more accurate. Even if the water were to turn acidic, it is believed that life in the oceans evolved when the oceans were mildly acidic with pH 6.5– to 7.0 (Krissansen-Totton *et al.*, 2018). On the time scale of thousands of years, boron isotope proxy measurements show that ocean pH was around 7.4 or 7.5 during the last glaciation (up to about 20,000 years ago) increasing to present-day values as the world warmed during deglaciation (Rae *et al.*, 2018). Thus, ocean biota appear to be resilient to natural long-term changes in ocean pH since marine organisms were exposed to wide ranges in pH.

2.2.2 Coral reef changes

There are concerns that a decreasing pH of sea water will reduce the calcification rate of coral reefs. But coral reefs already endure large swings in pH, partly due to daily photosynthetic activity in the reef; measured pH values range from 9.4 during the day to 7.5 at night (Revelle and Fairbridge, 1957). De'ath *et al.* (2009) reported that a portion of Australia's Great Barrier Reef (GBR, the world's largest coral reef ecosystem) had experienced a 14 percent decline in calcification since 1990. This was tentatively attributed to increasing water temperature and decreasing pH. But Ridd *et al.* (2013) showed that report to have resulted from a biased data analysis that, when corrected, showed no change in calcification rates. Nevertheless, the alarm produced by the original paper has persisted as evidenced by the large number of published citations (541) to the original study compared to only 11 citations to the correction (as of 30 April 2025).

The most recent annual summary of GBR conditions from the Australian Institute of Marine Science indicates that coral production has rebounded strongly (AIMS, 2023). Figure 2.5 shows the results of the AIMS surveys of hard coral cover, expressed as a percentage of the reef area. Much of the decline in the GBR before 2011 turned out to be due to intense tropical cyclone activity (Beeden *et al.*, 2015) as well as a string of marine heatwaves, agricultural runoff and invasive species (Woods Hole, 2023). Given the reported declines in GBR calcification between 1990 and 2009 and the continued increase in atmospheric CO₂ levels the rebound has surprised some observers.

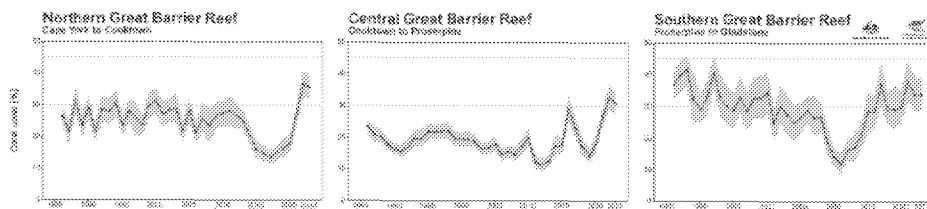


Figure 2.5 Hard coral cover of three regions of the Great Barrier Reef 1985 to 2023. Source: AIMS 2023.

It is being increasingly recognized that publication bias (alarming ocean acidification results preferred by high-impact research publications) exaggerates the reported impacts of declining ocean pH. An ICES Journal of Marine Science Special Issue addressed this problem with an article entitled, *Towards a Broader Perspective on Ocean Acidification Research*. In the Introduction to that Special Issue, H. I. Browman stated, “As is true across all of science, studies that report no effect of ocean acidification are typically more difficult to publish.” (Browman, 2016).

Similarly, a meta-analysis (Clements *et al.*, 2021) of the negative effects of ocean acidification on reef fish behavior found what they called a “decline effect”: initially dramatic conclusions published in prominent journals showing apparently large impacts of acidification tended to be followed up by subsequent studies on larger sample sizes yielding much smaller and typically non-existent effects. They call for their colleagues to improve research practices to counter the “decline effect”:

[The] vast majority of studies with large effect sizes in this field tend to be characterized by low sample sizes, yet are published in high-impact journals and have a disproportionate influence on the field in terms of citations. We contend that ocean acidification has a negligible direct impact on fish behavior, and we advocate for improved approaches to minimize the potential for a decline effect in future avenues of research (Clements *et al.*, 2021).

In summary, ocean life is complex and much of it evolved when the oceans were acidic relative to the present. The ancestors of modern coral first appeared about 245 million ago; as can be seen from Figure 2.2, CO₂ levels for more than 200 million years afterward were many times higher than they are today. Much of the public discussion of the effects of ocean “acidification” on marine biota has been one-sided and exaggerated. There is a known tendency for studies reporting dramatic effects on things like coral cover and fish behavior to get published in high-impact journals and receive widespread press coverage, then subsequent research rebutting those findings receives little attention.

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3 HUMAN INFLUENCES ON THE CLIMATE

Chapter Summary:

The global climate is naturally variable on all time scales. Anthropogenic CO₂ emissions add to that variability by changing the total radiative energy balance in the atmosphere.

The IPCC has downplayed the role of the sun in climate change but there are plausible solar irradiance reconstructions that imply it contributed to recent warming.

Climate projections are based on IPCC emission scenarios that have tended to exceed observed trends. Most academic climate impact studies in recent years are based upon the extreme RCP 8.5 scenario that is now considered implausible; its use as a business-as-usual scenario has been misleading.

Carbon cycle models connect annual emissions to growth in the atmospheric CO₂ stock. While models disagree over the rate of land and ocean CO₂ uptake, all agree that it has been increasing since 1959.

3.1 Components of radiative forcing and their history

3.1.1 Historical radiative forcing

A changing climate has been the norm throughout the Earth's 4.6-billion-year history. The Earth's temperature and weather patterns change naturally over timescales ranging from decades to millions of years. Natural variations in the surface climate originate in two ways. Internal climate fluctuations associated with circulations in the atmosphere and ocean exchange energy, water, and carbon between the atmosphere, oceans, land, and ice. External influences on the climate system include variations in the energy received from the sun and the effects of volcanic eruptions. Human activities influence climate through changing land use and land cover. Humans are also changing the composition of the atmosphere by emissions of CO₂ and other greenhouse gases and by altering the concentration of aerosol particles in the atmosphere.

The earth is warmed by the sunlight it absorbs and is cooled by the heat it radiates to space. Averaged over the Earth's surface, each of these processes involve power flows of about 240 Watts per square meter (W/m²). When they are in balance, there are no net external causes of warming or cooling. Both human and natural influences on the climate alter this balance and so cause the climate to change.

Influences on the Earth's energy balance at the top of the atmosphere are quantified by "radiative forcing", the extent to which they disturb the warming/cooling balance; a positive forcing warms while a negative forcing cools. The IPCC's estimated history of major components of radiative forcing since 1750 is shown in the following two figures from its AR6.

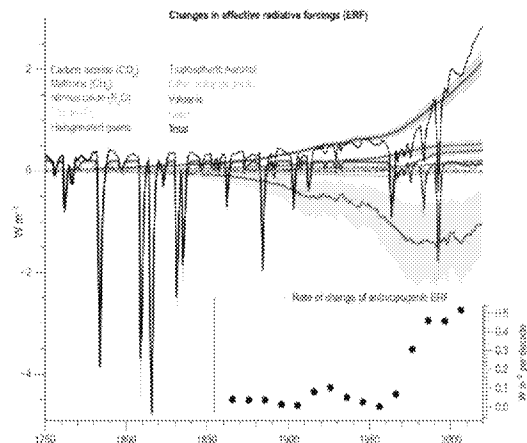


Figure 3.1.1: IPCC estimates of radiative forcing components over time. Shading indicates uncertainty ranges. Source: AR6 WGI Ch2 Fig. 10

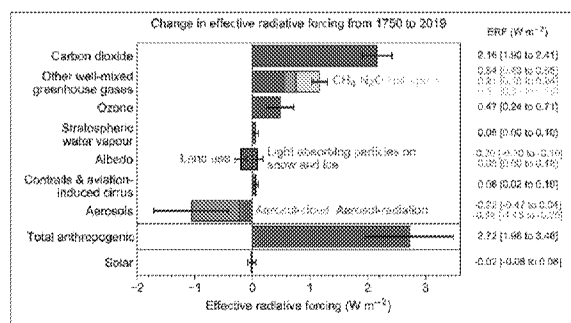


Figure 3.1.2 IPCC estimates of radiative forcing component changes from 1750 to 2019. Source: AR6 WGI Ch 7 Fig. 7-6.

These graphs show that the total radiative forcing is comprised of both natural and anthropogenic components. Carbon dioxide is the largest human influence on the climate and the one most relevant to the influence of fossil fuel use. It exerts a warming influence by decreasing the cooling power of the atmosphere. Emissions of CO₂ are accumulating in the atmosphere, as described in the following section, so that the warming influence is growing. Other greenhouse gases (methane, nitrous oxide, halogens, and ozone) act similarly, currently adding another 75 percent to CO₂'s warming. Aerosols exert an overall cooling effect, although with large uncertainties in the way they catalyze the formation of reflective clouds. As a result, understanding the causes of recent warming requires not just identifying the warming effects of CO₂, but also the more uncertain cooling effects of aerosols.

The IPCC assesses the change in the radiative forcing by the sun to be negligible, based on their preference for data reconstructions that imply minimal solar change since preindustrial times. But Connolly *et al.* (2021) reviewed sixteen different Total Solar Irradiance (TSI) reconstructions in the literature

covering the years 1600-2000; the reconstructions vary from almost no change in TSI to a relatively large upward trend. Those authors note that the variation in TSI reconstructions combined with variations in surface temperature reconstructions allows for inferences consistent with either no or most 20th century warming being attributable to the sun.

A particularly thorny issue is the gap in TSI data between 1989 and 1991 due to a delay in the launch of a monitor following the Space Shuttle Challenger disaster on January 28 1986. This delay prevented a replacement satellite from being launched in time to overlap with, and its readings to be intercalibrated with, the prior system (Zacharias 2014, Scafetta *et al.* 2019). This is called the ACRIM (Active Cavity Radiometer Irradiance Monitor) gap problem. The question of whether there is an upward trend in TSI over 1978 to 2018 hangs on how the ACRIM data gap is filled. Connolly *et al.* (2021) found that the IPCC's consensus statements on solar forcing were formulated prematurely through the suppression of dissenting scientific opinions.

Another natural radiative forcing component is volcanic aerosols, which exert an episodic cooling influence. Box 4.1 in the IPCC AR6 Report addresses the climate impact of volcanic eruptions, noting three explosive volcanic eruptions that occurred in the first half of the 19th century. This included the 1815 Tambora eruption that resulted in the 'year without summer', with multiple harvest failures across the Northern Hemisphere. There is uncertainty about the sign of the relatively small forcing due to the submarine volcano Hunga Tonga which erupted in 2022 (Jenkins *et al.* 2023, Schoeberl *et al.* 2024).

Figure 3.1.1 shows that the anthropogenic forcing component was negligible before about 1900 and has increased steadily since, rising to almost 3 W/m² today. However, this is still only about 1 percent of the unperturbed radiation flows, making it a challenge to isolate the effects of anthropogenic forcing; state-of-the-art satellite estimates of global radiative energy flows are only accurate to a few W/m².

Natural sources of global energy imbalance other than volcanoes and total solar irradiance (TSI) are not included in these graphs because they remain largely unknown.

3.1.2 Change in atmospheric CO₂ since 1958

Carbon dioxide's warming influence depends on how much "extra" CO₂ accumulates in the atmosphere- *i.e.*, its concentration above the preindustrial value of 280 ppm. The CO₂ level as recorded at the Mauna Loa observatory in Hawaii, generally used as the representative global average concentration, is available online at [HYPERLINK "<https://gml.noaa.gov/ccgg/trends/index.html>"]. The concentration was about 316 ppm at the start of the record in 1959 and is now about 430 ppm, a 36 percent increase. At the end of the last glaciation CO₂ levels had fallen to about 180 ppm. As discussed in Chapter 2, C3 plants begin dying at CO₂ levels below about 140 ppm and C4 plants at levels below 100 ppm, so if CO₂ levels had continued falling plant life would have been imperiled.

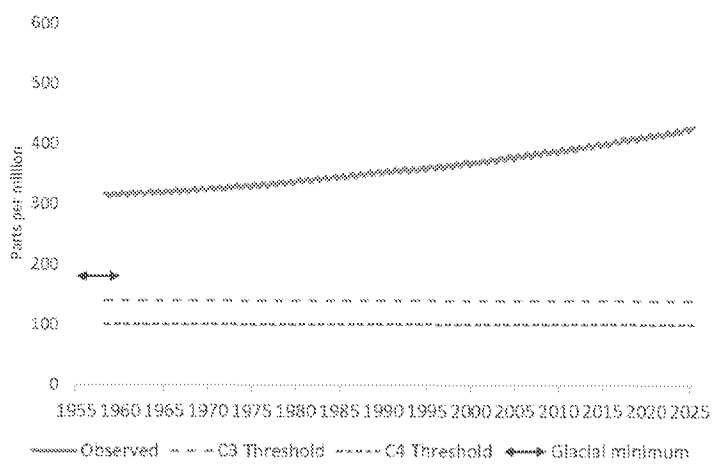


Fig. 3.1.3. Yearly average atmospheric CO₂ concentrations(1959-2025) in ppm measured at Mauna Loa (blue). C3 Threshold: Level below which C3 plants begin dying (140 ppm, see Chapter 2). C4 Threshold: Level below which C4 plants begin dying (100 ppm, see Chapter 2). Glacial minimum: Minimum level during recent glaciations (purple arrow). CO₂ data source: [[HYPERLINK "https://gml.noaa.gov/ccgg/trends/index.html"](https://gml.noaa.gov/ccgg/trends/index.html)]

The annual increase in concentration is only about half of the CO₂ emitted because land and ocean processes currently absorb “excess” CO₂ at a rate approximately 50 percent of the human emissions. Future concentrations, and hence future human influences on the climate, therefore depend upon two components: (1) future rates of global human CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere. We discuss each of these in turn.

3.2 Future emission scenarios and the carbon cycle

3.2.1 Emission scenarios

Assessing the dangers of future GHG emissions requires assumptions about what those emissions will be. Future emissions, and hence human influences on the climate, will depend upon future demographics, economic activity, regulation, and energy and agricultural technologies. Various assumptions about each of those lead to projections of greenhouse gas emissions and concentrations, aerosol concentrations, and changes in land use, which ultimately can be combined into assumptions about anthropogenic radiative forcing.

The great uncertainties about these many factors make it impossible to precisely predict future emissions. Instead, the IPCC has created various sets of scenarios meant to span a plausible range of possibilities for population, economy, and technologies. Recent versions of the scenarios are labeled by a number indicating the anthropogenic radiative forcing expected in 2100 under that scenario. Thus, a scenario labeled with a “6” corresponds to 6 W/m² of human-induced radiative forcing (warming) at the end of the century. (Recall current anthropogenic radiative forcing is about 2.7 W/m².)

Although the IPCC does not claim its emission scenarios are forecasts, they are often treated as such. Comparisons of past scenario groups against observations show that IPCC emission projections tend to overstate actual subsequent emissions. For the IPCC Third and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* was used; these were referred to as the SRES scenarios. McKittrick *et al.* (2012) showed that, when converted to per capita values, the SRES scenario emissions distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by the later analysis of Hausfather *et al.* (2019) who showed that observed atmospheric CO₂ concentrations tracked the low end of the SRES range and also of subsequent IPCC scenario ranges (Figure 3.2.1).

For AR5 the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCPs). These were identified by a number representing the increase in forcing and were thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying an anthropogenic radiative forcing in 2100 of 2.6 W/m²) describes a GHG concentration pathway leading to warming well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming from 1900 to 2100.

RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario in both the academic literature and popular media. It was therefore used to generate the reference outcome supposedly representing the 21st century world in the absence of increasingly stringent emission reduction policies. But RCP8.5 was intended as a low-probability high emissions scenario and its use as a business-as-usual baseline has been criticized as grossly misleading.¹ Hausfather and Peters (2020) writing in a commentary in *Nature*, pointed out that RCP8.5 was developed as an extreme worst-case, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting.

The implausibility of the RCP8.5 scenario was examined by Burgess *et al.* (2021). They noted that RCP8.5 has already diverged from observed trends in energy use and the near future trends diverge sharply from those of the International Energy Agency (IEA), which provides market-based projections of energy use for the coming decades. The IEA trends, which are based on plausible extrapolations of current economic and demographic trends, run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but that even lower emission scenarios are unlikely.

Widespread use of RCP8.5 has created an alarmist bias towards alarm in the climate impacts literature. The extent of this problem was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found that some 16,800 scientific papers published between 2010 and 2020 used the RCP8.5 scenario, with about 4,500 of the articles linking RCP8.5 to the concept of “business-as-usual”. Their analysis showed how RCP8.5 was misused not only by individual researchers, but also by influential science agencies like the IPCC and the U.S. National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets.

¹ This extreme scenario is useful for modelers, since a large forcing generates a large response (warming) making it easier to assess a model’s sensitivity. But that’s very different than claiming it is a plausible future outcome.

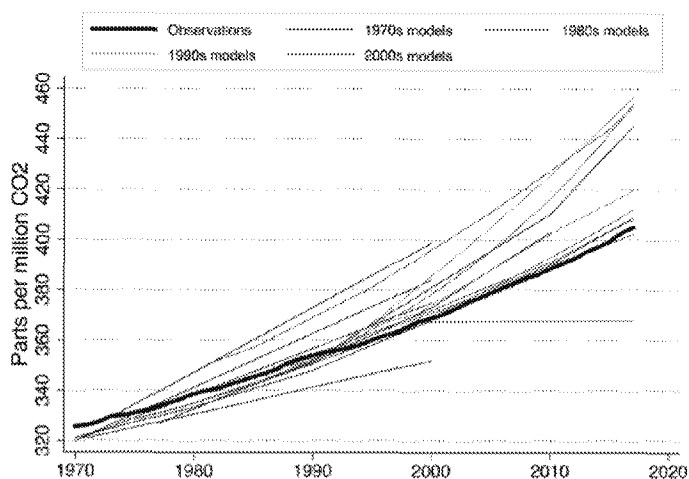


Figure 3.2.1 Comparison of observed atmospheric CO₂ levels (black line) with scenario projections (colored lines, mainly IPCC) since the 1970s. Source: Hausfather *et al.* (2019) Figure S4.

Pielke and Ritchie (2020) reported new studies using RCP8.5 were published at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude that the climate research community has spent a decade “committing scientific resources to science fiction” and that “The scientific literature has become imbalanced in an apocalyptic direction.”

The IPCC developed a new set of scenarios for AR6, the “Shared Socioeconomic Pathway” (SSP) scenarios, which have continued the bias shown in the RCP and SRES scenarios. Figure 3.2.2 shows total global observed CO₂ emissions compiled by the International Energy Agency (IEA) merged with the emission projection from the IEA taking account of energy use projections and current policies. The other lines show the range of IPCC SSP scenarios (SSP1-SSP5). As of 2023, global CO₂ emissions have been tracking well below SSP7.0 and are even below SSP2-4.5.

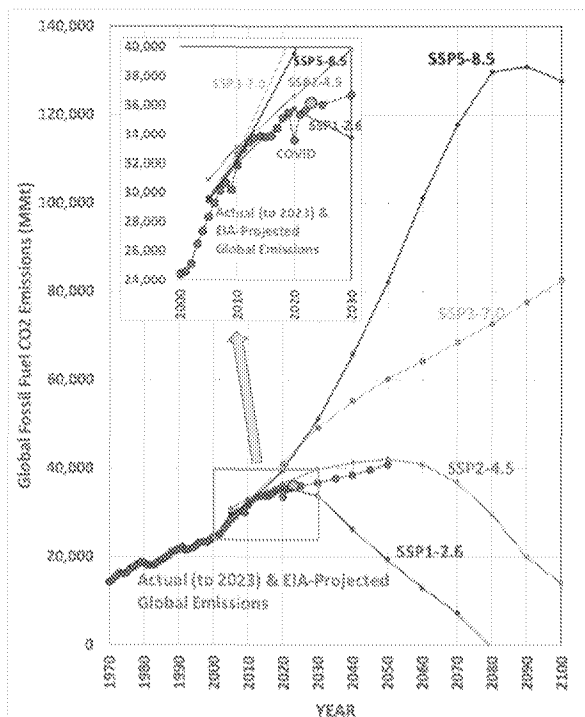


Figure 3.2.2. Observed and projected CO₂ emissions. Source: IPCC (SSP scenarios) and Energy Information Administration (EIA). Green: observed historical emissions and EIA projections. Other lines: SSP1-5. Data source: Friedlingstein *et al.* (2024).

3.2.2 The carbon cycle relating emissions and concentrations

Carbon dioxide emissions from fossil fuel burning (and to a lesser extent deforestation and cement production) have led to steadily increasing CO₂ concentrations in the atmosphere, as shown in Fig. 3.1.3. The relation between emissions and concentration is determined by the global carbon cycle of land and ocean processes that exchange carbon with the atmosphere. Our understanding of these processes was reviewed by Crisp *et al.* (2021).

There are about 850 Gt of carbon (GtC) in the Earth's atmosphere², almost all of it in the form of CO₂. Each year, biological processes (plant growth and decay) and physical processes (ocean absorption and outgassing) exchange about 200 GtC of that carbon with the Earth's surface (roughly 80 GtC with the land and 120 GtC with the oceans). Before human activities became significant, removals from the atmosphere were roughly in balance with additions. But burning fossil fuels (coal, oil, and gas) removes carbon from the ground and adds it to the annual exchange with the atmosphere. That addition (together with a much

² Because CO₂ is chemically transformed through the course of the carbon cycle, it is more convenient to track atoms of carbon rather than molecules of CO₂. One gigatonne of carbon (GtC) is equivalent to about 3.7 Gt of CO₂.

smaller contribution from cement manufacturing) amounted to 10.3 GtC in 2023, or only about 5 percent of the annual exchange with the atmosphere.

The carbon cycle accommodates about 50 percent of humanity's small annual injection of carbon into the air by naturally sequestering it through plant growth and oceanic uptake, while the remainder accumulates in the atmosphere (Ciais *et al.*, 2013). For that reason, the annual increase in atmospheric CO₂ concentration averages only about half of that naively expected from human emissions.

To project future CO₂ concentrations in the atmosphere, and hence future human influences on the climate, it is important to know how the carbon cycle might change in the future. The historical near constancy of that 50 percent fraction means that the more CO₂ humanity has produced, the faster nature removed it from the atmosphere. That 50 percent fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Niño, La Niña, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert *et al.*, 2004).

The main processes that remove excess CO₂ from the atmosphere are increased growth of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein *et al.*, 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a "global greening" phenomenon (Chapter 2.1) observed by satellites since monitoring of global greenness began in 1982.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be measured reliably. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp *et al.* (2021).

CO₂ uptake by land processes

The uptake of extra CO₂ from the atmosphere by land surface processes (as also inferred from global greening) has been modeled with 20 different dynamic global vegetation models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). As seen in Fig. 3.2.3, all of those models agree that vegetation and soils have been sequestering carbon from the atmosphere. But we also see that the long-term trends over 1959 to 2023 (65 years) vary widely between models, by nearly a factor of 7. This demonstrates that there remains considerable uncertainty in how fast land processes are removing CO₂ from the atmosphere, which in turn creates uncertainty in future atmospheric CO₂ concentrations, which then produce uncertainty in climate model simulations of future climate change.

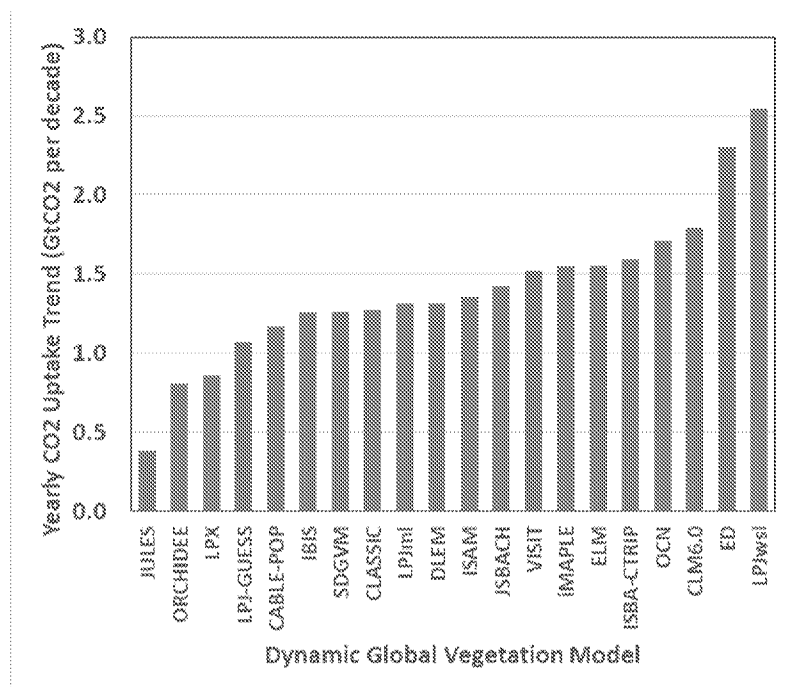


Figure 3.2.3 Trends of annual CO₂ uptake (GtCO₂ per year per decade) by land processes during 1959-2023 simulated by 20 different dynamic global vegetation models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

CO₂ uptake by ocean processes

The uptake of extra CO₂ from the atmosphere by ocean processes has been modeled with 10 different ocean biogeochemistry models, the outputs of which are updated every year by the Global Carbon Project (Friedlingstein, 2024). Like the results from the land models, all of the ocean models agree that the global oceans have been sequestering carbon from the atmosphere at an increasing rate during 1959-2023 (Fig. 3.2.4). Unlike the land models, however, the ocean models show much better agreement with each other, with the model producing the fastest increasing CO₂ uptake being only 65 percent faster than the model with the most slowly increasing CO₂ uptake. In spite of the relative agreement among models, Friedlingstein *et al.* (2022) notes that there is substantial discrepancy between the different methods on the strength of the ocean sink over the last decade, particularly in the Southern Ocean.

Note that the average trend in CO₂ uptake across all land models in Fig. 3.2.3 is 25 percent larger than the average trend in ocean uptake. This suggests land processes are increasing in their ability to remove CO₂ faster than ocean processes are increasing their CO₂ sequestration.

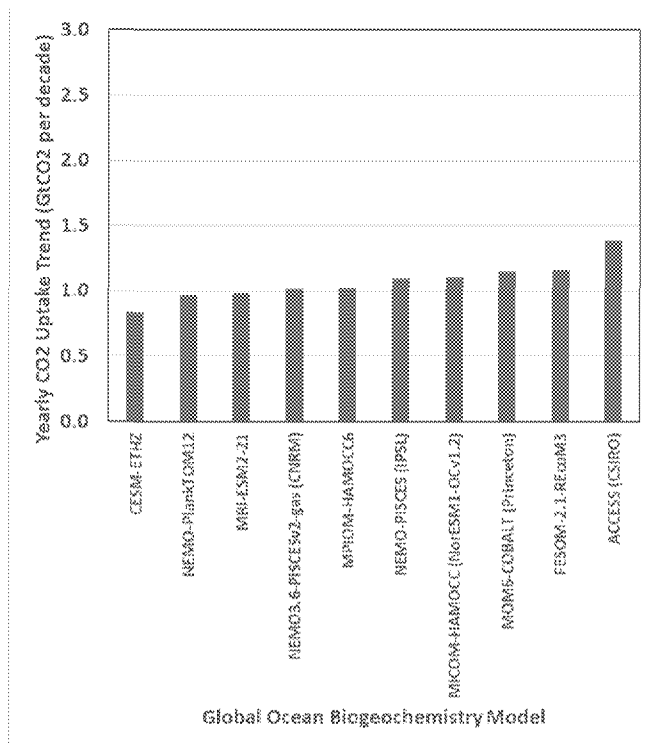


Figure 3.2.4 Trends of annual CO₂ uptake (GtCO₂ per year per decade) by ocean processes during 1959-2023 simulated by 10 different ocean biogeochemistry models periodically reported by the Global Carbon Project (Friedlingstein, 2024).

3.3 Urbanization influence on temperature trends

Historical temperature data over land has been collected mainly where people live. This raises the problem of how to filter out non-climatic warming signals due to Urban Heat Islands (UHI) and other changes to the land surface. If these are not removed the data may ~~may in fact~~ over-attribute observed warming to greenhouse gases. The IPCC acknowledges that raw temperature data are contaminated with UHI effects but claims to have data cleaning procedures that remove them. It is an open question whether those procedures are sufficient.

AR6 downplayed this issue by saying (WGI p. 235) that no recent evidence had emerged to alter the AR5 finding that urbanization causes an upward bias of no more than 10 percent in the global land surface warming trend. AR5 (WGI p. 189) also cited the 10 percent upper bound without citing a source. AR4 (WGI p. 244) cited Jones *et al.* (1990) and Peterson *et al.* (1999) as the basis of the claim. Peterson *et al.* had failed to find any difference in trends between rural and urban samples, although their definition of rural included local populations up to 10,000 persons while the relative influence of urbanization begins well below that (Spencer *et al.*, 2025). Jones *et al.* compared rural/urban warming in three regions: Eastern Australia, Eastern China and Western Soviet Union. Their definition of “rural” included towns of up to

10,000 in the former Soviet Union and up to 100,000 in China. They found relative warming biases greater than 10 percent in these areas but conjectured that the urbanization effect averaged over the areas they did not examine would bring the global land bias to under 10 percent of the observed warming trend.

Several papers appeared in print prior to the IPCC AR4 that argued that the warming effect of UHIs added a relatively large (30-50%) component to observed warming and was not simulated by climate models (de Laat and Maurellis 2006, McKittrick and Michaels 2007). These findings were based on correlations between locations of maximum warming over land with locations of maximum socioeconomic development. AR4 asserted (p. 244) that these correlations were an artefact of natural atmospheric circulations and were in fact statistically insignificant, and on that basis set the findings aside. Their claim was controversial because it was presented with no supporting evidence. McKittrick (2010) and McKittrick and Nierenberg (2010) showed that taking into account various conjectured alternative explanations for the correlations did not affect their significance. AR5 (p. 189) conceded that AR4 had provided “no explicit evidence” for its assessment and further acknowledged, based on these papers, that there was “significant evidence for such contamination of the record” i.e. a warming bias in the land record. However as already noted, elsewhere in the AR5 report they carried forward AR4 claim that it was less than 10 percent of observed warming. Further they provided no caution about using the land record for climate measurement despite conceding the evidence for UHI contamination. Recently Soon *et al.* (2023) estimated an urbanization bias in the Northern Hemisphere land record over 1850-2018 sufficient to increase the trend in the blended record from 0.55°C to 0.89°C per century.

Some studies providing evidence against UHI contamination compared warming rates between rural and urban locations (Jones *et al.* 1990, Peterson *et al.* 1999, Wickham *et al.* 2013). It is not known whether such methods would be capable of detecting UHI bias even when present. The influence of UHI warming is logarithmic in population, in other words it is strongest at low population density then levels off as local urbanization expands (Oke 1973, Spencer *et al.* 2025). Hence failure to find a difference in warming rates between urban and rural stations does not prove the absence of UHI contamination. McKittrick (2013) provided an empirical demonstration in which the rural/urban trends were not significantly different in a data set shown on other grounds to be contaminated with UHI bias.

Parker (2006) examined a sample of urban locations and found no difference in trends between subsets partitioned according to nighttime wind speed, concluding on this basis that urbanization could not be a significant factor. Here again the question is whether such a method would find UHI bias even if present. McKittrick (2013) presented an example in which UHI-contaminated data did not exhibit significant trend differences when stratified according to wind speed.

The challenge in measuring UHI bias is relating local temperature change to a corresponding change in population or urbanization, rather than to a static classification variable such as rural or urban. Spencer *et al.* (2025) used newly available historical population archives to undertake such an analysis and found evidence of significant UHI bias in U.S. summertime temperature data.

In summary, while there is clearly warming in the land record, there is also evidence that it is biased upward by patterns of urbanization and that these biases have not been completely removed by the data processing algorithms used to produce climate data sets.

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PART II: CLIMATE RESPONSE TO CO₂ EMISSIONS

4 CLIMATE SENSITIVITY TO CO₂ FORCING

Chapter Summary

There is growing recognition that climate models are not fit for the purpose of determining the Equilibrium Climate Sensitivity (ECS) of the climate to increasing CO₂. The IPCC has turned to data-driven approaches including historical data and paleoclimate reconstructions, but their reliability is diminished by data inadequacies.

Data-driven ECS estimates tend to be lower than climate model-generated values. The IPCC AR6 upper bound for the likely range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by paleoclimatic data. The IPCC AR6 lower bound for the likely range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound is ~~less well~~ justified; evidence since the AR6 finds the lower bound of the likely range to be around 1.8°C.

4.1 Introduction

The climate's response to increasing concentrations of CO₂ is central to the scientific debate on anthropogenic climate change, and so also to the public debate on "climate action." The simplest measure of that response is the rise in the global average surface temperature, quantified by the Equilibrium Climate Sensitivity (ECS). ECS is defined as the amount of warming expected in response to a doubling of CO₂ from its pre-industrial concentration of 280 ppm, after all climate components have had time to adjust. Some components, like temperatures in the lower atmosphere (troposphere), adjust rapidly, while others such as the deep ocean and cryosphere might take as long as centuries. A related measure, the Transient Climate Response (TCR), better describes the shorter time scales; it is defined as the amount of warming when the CO₂ concentration is doubled by rising one percent annually for 70 years.

The 1979 Charney Report for the U.S. National Academy of Sciences (National Research Council 1979) proposed that the most likely ECS was $3.0 \pm 1.5^\circ\text{C}$. The IPCC repeatedly reaffirmed that range with only minor variations until its most recent AR6. AR5 termed 1.5–4.5°C as the *likely* range (66 percent probability) and stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and *very unlikely* (90 percent probability) to exceed 6.5°C.

The uncertainty in ECS has remained stubbornly wide, despite many individual studies that claimed to narrow it (Hausfather 2023). Most recently, AR6 narrowed the *likely* range to 2.5–4.0°C and deemed the *very likely* range to be 2.0–5.0°C. This narrowing on the low end is disputed, as will be discussed below.

Uncertainties in ECS are highly consequential for policy making. As will be discussed in Chapter 11, economic models use ECS values to project the costs of CO₂ emissions. The traditional value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, sufficient to justify some policy actions, but mostly deferred to later in this century. If ECS is very high (above 4.5°C) immediate aggressive emission controls become more imperative, whereas no CO₂ emission controls are economically justifiable for ECS below 2.0°C (Dayaratna *et al.* 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

By itself, the equilibrium warming effect of a doubling of atmospheric CO₂ is slightly more than 1 °C (Soden and Held 2006). Larger values of ECS arise from positive feedbacks that amplify the CO₂ warming. Water vapor feedback is positive: a warmer atmosphere ~~may~~ ^{will} have more water vapor, which itself is a powerful greenhouse gas. Warmer temperatures also result in less snow and sea ice cover, allowing the

Earth to absorb more of the sun’s radiation. Some simple estimates of these feedbacks increase the ECS to around 2°C (Sherwood *et al.*, 2020). Larger values of ECS are associated with positive cloud feedbacks.

Climate scientists use multiple lines of evidence to determine the Equilibrium Climate Sensitivity:

- Climate model simulations
- Historical observations
- Paleoclimatic reconstructions
- Process understanding of feedbacks

4.2 Model-based estimates of climate sensitivity

The ECS ranges given in IPCC AR4 and AR5 were obtained primarily by examining the behavior of large-scale climate models, also called General Circulation Models (GCMs). However, the IPCC changed course in its AR6 when it turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using GCMs to try to determine the Earth’s climate sensitivity.

In essence, ECS is an emergent property of GCMs – that is, it is not directly parameterized or tuned, but rather emerges in the course of the simulation. But historically, collections of parameterizations have been chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes, particularly in AR4 and to a lesser extent in AR5. THESE SENTENCES ARE CONTRADICTIONARY AS WRITTEN. I’VE TRIED TO FIX, AND DO WE HAVE SUPPORT FOR THE STATEMENTS ABOUT AR4.5? Otherwise plausible GCMs and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model’s climate sensitivity being outside an accepted range. For example, even in a CMIP6 model, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute (MPI) climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming: an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by **targeting an ECS of about 3 K using cloud feedbacks**, as opposed to tuning the aerosol forcing.”

In other words, the MPI modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

As noted, direct warming from CO₂ doubling is only about 1°C (Soden and Held 2006); further warming arises from climate feedbacks that are not explicitly resolved by the GCM but rely on parameterizations of physical processes. Higher values of ECS arise primarily from assumed positive cloud feedbacks, whereas the magnitude and even the sign of the feedbacks are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for GCMs to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity need for of such long

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simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂.

The spread of ECS values from the CMIP5 ensemble of climate models used in the AR5 was 2.0–4.7°C; that range increased for the CMIP6 models used in the AR6 to between 1.8 and 5.7°C (Chen *et al.*, 2021, Scafetta 2021, see Figure 4.1). Far from settling the model-based sensitivity of climate system, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka *et al.*, 2020)

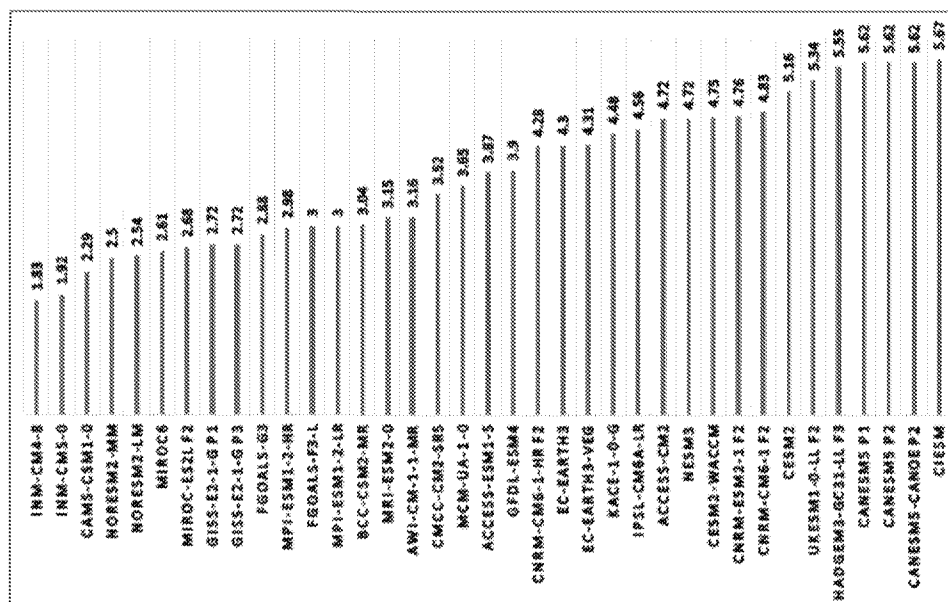


Figure 4.1 Equilibrium Climate Sensivities in °C of 37 climate models from the CMIP6 ensemble. Identifiers for the various models appear along the horizontal axis. From (Scafetta, 2021)

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on data-driven methods.

4.3 Data-driven estimates of climate sensitivity

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto *et al.*, 2013). Using this information, a simple empirical model

called an Energy Balance Model can be employed. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and good data is only available for recent decades. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect; see Figures 3.1.1, 3.1.2). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz *et al.*, 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂.

Paleoclimate proxies are also used to evaluate the sensitivity of past climates by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states ~~may not~~ not be applicable to the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood *et al.* (2020) that combined historical data and paleoclimate proxies with the process-based approach and yielded a best estimate of 3.1°C with a *likely* range of 2.6–3.9°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood *et al.* analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood *et al.* and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An argument emphasized in AR6 is that data-driven ECS estimates might understate the future warming response to GHGs because of a so-called “pattern effect” (Forster *et al.*, 2021). The tropical Pacific is believed to strongly influence the overall efficiency with which the Earth radiates heat to space, but some regions remove heat more efficiently than others. If the west-to-east temperature gradient in the tropical Pacific is weakened in a warming climate, warming would concentrate where heat is less efficiently removed, raising ECS.

Most climate models simulate that rising GHGs will weaken the west-east temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value. However, Seager *et al.* (2019) pointed out that, contrary to models, the west-east temperature gradient has been strengthening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee *et al.* (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate ~~may not~~ be lower than current estimates.

4.4 Transient Climate Response

The Transient Climate Response (TCR) provides a more useful observational constraint on climate sensitivity. TCR is the global temperature increase that results when CO₂ is increased at an annual rate of 1 percent over a period of 70 years (*i.e.*, doubled gradually). Relative to the ECS, observationally determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (*e.g.*, ice sheets). TCR is more generally related to peak warming and better constrained by historical warming than ECS. IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. In contrast to ECS, the upper bound of TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) are 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

As will be discussed in Chapter 5, a real-world ECS smaller than the model average is supported by studies that show climate models on average overestimate the observed surface and troposphere warming over the past 50 years. Lower sensitivities also align with evidence from consistent fingerprinting (Chapter 8), where model responses need to be downscaled to align with observed trends. ~~DOESN'T BELONG IN TCR SECTION NOT NEEDED IN THIS CHAPTER~~

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5 MODELS VERSUS OBSERVATIONS IN THE RECENT PAST

Chapter summary

Climate models show warming biases in many aspects of their reproduction of the past several decades. In response to estimated changes in forcing they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

Climate models also produce too much recent stratospheric cooling, invalid hemispheric albedos, too much snow loss, and too much warming in the Corn Belt. The IPCC has acknowledged some of these issues but not all.

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. To assess the fitness of climate models for this purpose, it is reasonable to ask how well they reproduce the current climate and its variations over the past century. The box “Climate modeling” gives some detail on how climate models work.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three, as we discussed in the previous chapter. This range of disagreement among models has not decreased for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends; ability to reproduce the vertical warming profile; and ability to reproduce other climate features such as snowfall. In all cases a persistent finding is that models on average err on the side of too much warming in response to estimated historical forcings.

BOX: Climate modeling

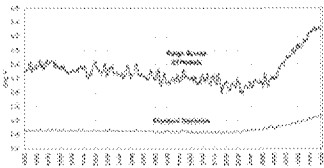
Most climate models, except for the simplest ones, represent Earth's land surface using a grid of squares on the order of 100 km wide. To simulate the atmosphere, typically 30 or more grid boxes are stacked above these squares. The ocean is modeled using a similar but finer grid, resulting in tens of millions of grid boxes for the atmosphere and oceans.

The computer models, based on physical laws, calculate how air, water, and energy move between grid boxes over time. The time step can be as small as 10 minutes, and repeating this process millions of times allows the simulation of climate over centuries. Running these models, even on the most powerful supercomputers, can take months. Comparing simulation results with historical climate data helps assess the accuracy of a model, while projections into the future estimate climate changes under assumed human and natural influences.

Despite sounding straightforward, climate modeling is highly complex. Many critical processes occur at scales smaller than the grid size. For instance, the flows of sunlight and heat in the atmosphere depend strongly on cloud cover. Since tracking individual clouds is impractical, researchers must make "subgrid" assumptions about the distribution of clouds in each grid box. Snow and ice cover, which affects how much sunlight is reflected or absorbed by the surface, is another subgrid factor.

Each subgrid assumption requires numerical parameters, which must be carefully set. Modelers initially estimate these parameters based on physics and observed climate patterns, then run the model. Because early results often diverge significantly from real-world observations, they "tune" these parameters to better match observed climate features. Different modeling teams use distinct assumptions and tuning strategies, leading to varied outcomes. Tuning is a necessary but delicate aspect of climate modeling, as it is for any complex system. Poor tuning can result in inaccurate simulations, while excessive tuning risks artificially steering results toward predetermined conclusions.

The spread of model indicators—Earth's 1880 (Figure 5.1), warming was only processes.



very wide. One of the most basic about 3°C across CMIP6 models prior to 2020, warming to over 4 °C. For comparison 20th century tantial differences among models' physical

Figure 5.1 CMIP6 Average surface temperature range across 33 models and standard deviation using SSP5-85 scenario. Data from KNMI Climate Explorer website at [[HYPERLINK "https://climexp.knmi.nl/start.cgi"](https://climexp.knmi.nl/start.cgi)].

Beyond the models' ability to reproduce features of today's climate, the critical issue for society is how well they predict responses to subtle human influences, such as greenhouse gas emissions, aerosol cooling, and land-use changes. The most crucial aspect that models must capture correctly is "feedbacks." These occur when climate changes either amplify or suppress further warming. In general, the modeled net effect of all feedbacks doubles or triples the direct warming impact of CO₂.

5.2 Surface warming

A straightforward test of a climate model's validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 5.2 is reproduced from Scafetta (2023), that groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

The leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

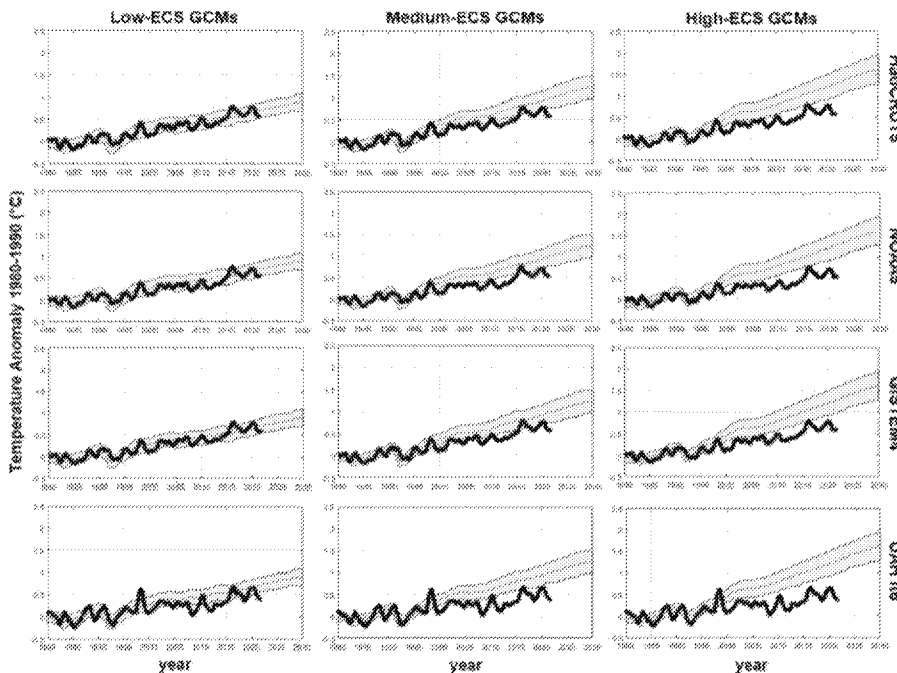


Figure 5.2: Model-Observational comparisons for Earth's surface warming. The columns correspond to model groups showing low-ECS to high-ECS, while the rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source. Source: Scafetta (2023) Fig.2.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by comparing trends in surface temperature data products with those in individual climate models, as summarized in Figure 5.3. It is seen that most climate models show substantially more warming than the observations.

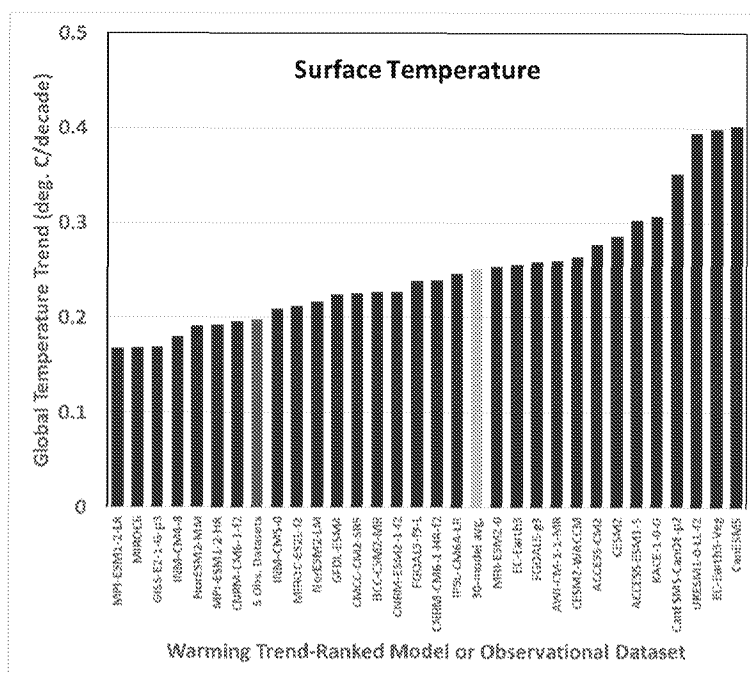


Figure 5.3 Global surface air temperature trends ($^{\circ}\text{C}/\text{decade}$), 1979–2024, from various CMIP6 climate models (red, 30-model average in orange); and the average of three thermometer datasets (HadCRUT5, NOAA Global Temp, and Berkeley 1 deg.) and two reanalysis datasets (ERA5 and NCEP/NCAR R1) in blue. Data source: <https://climexp.knmi.nl/start.cgi>.

5.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the tropical troposphere. This region is an important test of climate models since this is where the signal of anthropogenic greenhouse warming emerges first and most strongly. Biases in tropospheric trends indicate model flaws in heat transfer processes that carry over to surface warming biases.

The discrepancy was flagged as a serious inconsistency in the first U.S. Climate Change Science Program report (Karl *et al.* 2006) and has been mentioned in every IPCC report since, but the discrepancy has gotten worse over time, and the bias is now global. McKittrick and Christy (2020) compared tropospheric warming trends in CMIP6 climate models to observed trends from satellites, weather balloons and reanalysis systems. Every model overpredicted the average observed warming trend over 1979-2014 in both Lower- and Mid-Troposphere layers, both globally and in the tropics. In most individual models the bias was statistically significant and on average across models it was highly significant.

Figure 5.4 presents the comparisons with data updated to 2024 (McKittrick and Christy 2025). The recent warm years moved the observed trend up slightly and widened the trend confidence intervals but the overall pattern remains the same: model bias is towards too much warming, in most cases the difference is statistically significant and on average the bias is statistically highly significant. McKittrick and Christy (2020) also showed that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If future climate models were to realistically represent global tropospheric warming, they would likely be less sensitive than even the low-ECS members of the CMIP6 ensemble.

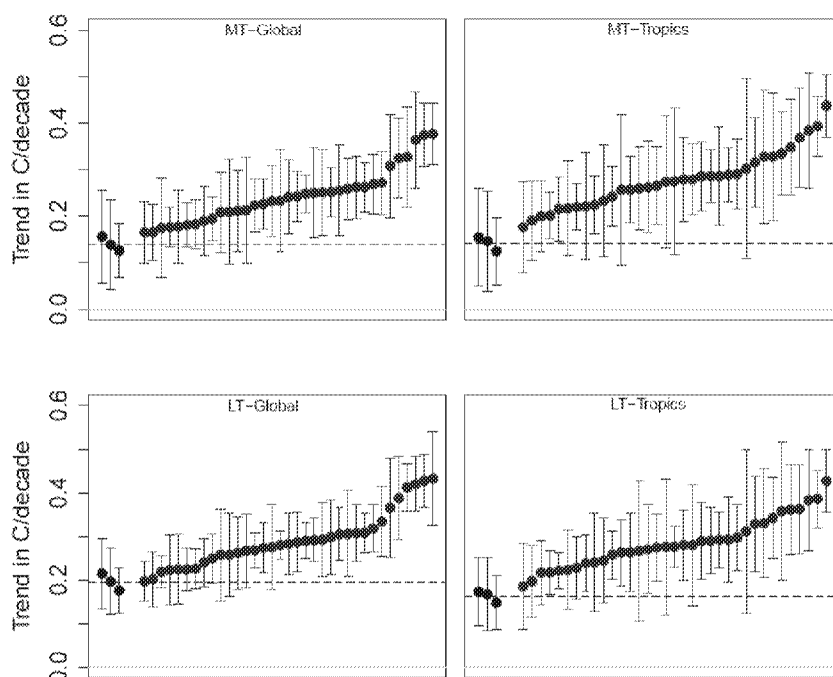


Figure 5.4: Observed versus CMIP6 modeled warming trends (°C/decade 1979-2024) in the global and tropical lower (LT) and mid-troposphere (MT). Uses methodology of McKittrick and Christy (2020) on data updated from 2014 to 2024. Blue dots: warming trends with 95 percent confidence intervals for 3 data products (radiosondes, reanalysis, and satellites). Blue dashed line: warming trend average for 3 observed series. Red dots: modeled warming trends with 95 percent confidence intervals in 35 models arranged lowest to highest.

As mentioned previously, the IPCC has long acknowledged the model-observation mismatch. For example, AR6 pp. 443-444 offers this on the tropical troposphere (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell *et al.*, 2013, 2020; Santer *et al.*, 2017a, b; McKittrick and Christy, 2018; Po-Chedley *et al.*, 2021). Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200 hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley *et al.*, 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley *et al.*, 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015). I DON'T THINK THIS PARA IS NEEDED? FOLLOWING PARA PACKS A BIGGER PUNCH PER ROSS' RECENT EMAIL, WE'LL KEEP IT

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell *et al.*, 2013, 2020; Santer *et al.*, 2017a, b; Suárez-Gutiérrez *et al.*, 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell *et al.*, 2013; Po-Chedley *et al.*, 2021). ... Hence, we assess with *medium confidence* that CMIP5 and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

Notably, despite the accumulation of evidence of excess model warming the IPCC assigns only *assigns medium confidence* to the existence of a warming bias.

5.4 Vertical temperature profile mismatch

Another important model-observational discrepancy is the excess amplification with altitude found in climate models. The comparison was in the IPCC AR5 Chapter 10, although only in the online supplement (Figure 10.SM.1) and only in a figure whose formatting obscured the point. Figure 10.SM.1 is not referenced in the main IPCC report nor in any summary so readers would not have been aware of it. Although not apparent at first glance, it shows that the 1979–2010 warming in the lower troposphere is so small as to be consistent with no GHG forcing at all and is inconsistent with the model runs that do have GHG forcing. In Figure 5.6 we adapt IPCC AR5 Figure 10.SM.1 to draw out this critical point.

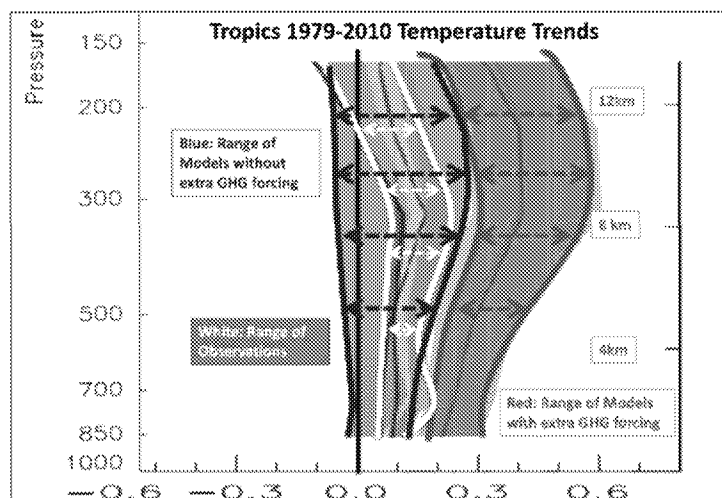


Figure 5.6: Vertical warming pattern for tropics (20S to 20N). Source: Annotated version of IPCC AR5 Figure 10.SM.1

Figure 5.6 compares model and observational temperature trends by altitude between 20S and 20N (the tropics). In this region where the models say the warming should be strongest, the observations (shown here in white) lie within the blue “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the base of the stratosphere, observed warming trends are so small as to be consistent with the output of models that have no anthropogenic CO₂ warming, and inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.7. Modeled temperature trends exceed observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.7 is the tropical tropospheric temperature (TTT) average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again, the observed trends lie below the entire model range.

The wide range of choices made by modelers to characterize the physical processes in the models (see Box: Climate Modeling in Section 5.1 above) is seen by the large spread of trends in the middle troposphere, ±40 percent about the median (Fig. 5.7). This vividly illustrates the uncertainties in attempts to model (parameterize) a complex system involving turbulence, moist thermodynamics, and energy fluxes over the full range of the tropical atmosphere’s time and space scales.

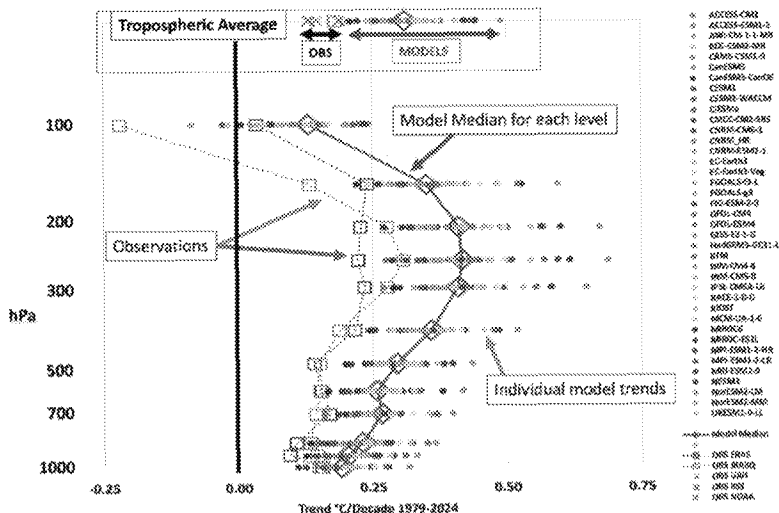


Figure 5.7: Modeled versus observed warming, tropical troposphere. Source: updated from Christy and McNider (2017) including data through 2024. Red line: model average. Green and blue lines: observational series (reanalysis).

This discrepancy has been the source of much controversy, with some arguing that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface (Santer et al. 2008). But there is good evidence that models also exaggerate the amplification rate. Klotzbach *et al.* (2009), showed that models project greater amplification with altitude than is observed. This result was subsequently confirmed by detailed time series analysis (Vogelsang and Nawaz 2016) ~~who~~ which found that the model-observational difference is statistically significant.

The atmosphere’s temperature profile is a case where models are not merely uncertain but also show a common warming bias relative to observations. This suggests that they misrepresent certain fundamental feedback processes.

The IPCC AR6 did not assess this issue.

5.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. ~~The IPCC~~ The IPCC AR6 acknowledged that cooling had been observed but only until the year 2000. The stratosphere has shown some warming since, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states:

Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with the bulk of the decrease prior to 2000. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend,

found by Steiner *et al.* (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona *et al.* (2018) show weak increases over 2000–2015 in the very lowermost stratosphere sampled by radiosondes...

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona *et al.* (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

In response to continued greenhouse gas increases and stratospheric ozone depletion, climate models project continued tropospheric warming and stratospheric cooling over the coming decades. Global average satellite observations of lower stratospheric temperatures exhibit no significant trends since the turn of the century. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.

A combination of tropospheric warming and stratospheric cooling is a ~~commonly cited~~ commonly cited “fingerprint” of anthropogenic warming. Stratospheric warming since 2000 coincides with continued surface and tropospheric warming, a pattern that is not found in climate model simulations and is not apparently consistent with the anthropogenic fingerprint.

5.6 Snow cover mismatch

Data compiled by the Rutgers University SnowLab ~~show~~ show that Northern Hemisphere winter snow cover is not decreasing (Figure 5.8); if anything, it shows an increasing trend.

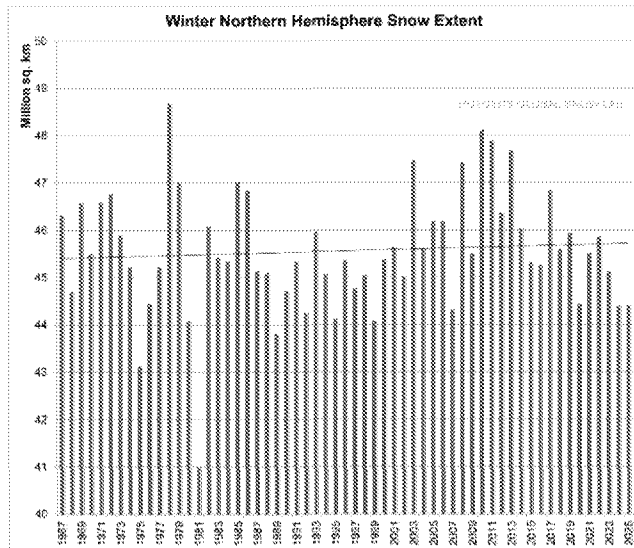


Figure 5.8: Northern Hemisphere Winter Snow extent.

Source: [[HYPERLINK](https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1)

"https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1"]
(accessed May 27, 2025)

Yet models project declining Northern Hemisphere snow cover in a warming climate, as described by Connolly *et al.* (2019).

The climate models were found to poorly explain the observed trends [in Northern Hemisphere snow cover]. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions. Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant.

AR6 largely confines its discussion of changing Northern Hemisphere snow cover extent (SCE) to the Spring season, for which models and observations agree on a downward trend. Regarding Winter changes it remarks as follows (AR6 WGI Ch. 2 p. 344):

Assessment of SCE trends in the NH since 1978 indicates that for the October to February period there is substantial uncertainty in trends with the sign dependent on the observational product. Analysis using the NOAA Climate Data Record shows an increase in October to February SCE (Hernández-Henríquez *et al.*, 2015; Kunkel *et al.*, 2016) while analyses based on satellite borne optical sensors (Hori *et al.*, 2017) or multi-observation products (Mudryk *et al.*, 2020) show a negative trend for all seasons.

AR6 WGI Chapter 9 (p. 1284) points out that the NOAA Climate Data Record showing increased fall and winter SCE is inconsistent with land-based observations and model-based data sets. It notes that using optical satellite imagery to infer SCE in winter is challenging due to cloud cover and decreased solar illumination in winter months. Focusing on the Pacific Coast states (CA, OR and WA) cold season mountain snowfall that melts in spring and summer provides a substantial portion of warm season water resources. A comprehensive reconstruction of snowfall for the main source regions (Cascades and Sierra Nevada Mountains) indicates no significant trends in annual totals since the late 19th century (Christy 2022).

In summary, the up-to-date Rutgers SCE database indicates a mismatch between models and observations. Further work to reconcile conflicting trends in observational data sets is required.

5.7 Hemispheric symmetry of the planetary albedo

The planetary albedo is the fraction of incoming solar radiation reflected by the Earth back to space. It is an important element of the radiative energy balance and influences whether the planet will warm or cool over time. The planetary albedo is typically estimated at around 0.30; variations on the scale of 0.01 correspond to changes in solar forcing of about 3 W/m^2 , an amount larger than current anthropogenic forcing. It has long been noted that models disagree with each other and with observations on the value of the global planetary albedo (Stephens *et al.* 2015).

An intriguing property of the Earth's albedo is that, on average, the Northern Hemisphere (NH) and Southern Hemisphere (SH) have had nearly the same albedo, at least throughout the fifty-year satellite record (Stephens *et al.*, 2015). This symmetry is surprising, because the SH has much more ocean than land. Since ocean is less reflective than land, the NH should have higher albedo. Clouds (which are highly reflective) are more common in the NH and so compensate the surface albedo imbalances of the two hemispheres. Datseris and Stephens (2021) show that this cloud compensation comes from the extra-tropical storm tracks of the SH, which are cloudier than those of the NH. While the mechanism for this hemispheric symmetry is unclear, it likely operates on large temporal and spatial scales.

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The hemispheric symmetry of the albedo is a simple gross metric for climate models. Rugenstein and Hakuba (2023) defined that metric as the difference between the NH and SH annual mean albedos, expressed as Wm^{-2} of the reflected sunlight, and compiled it for the CMIP6 climate models, as shown in Figure 5.9. Most of the CMIP6 models do not reproduce the small observed asymmetry (about 0.1 Wm^{-2}) and even disagree as to which hemisphere is more reflective. Moreover, the magnitude of the asymmetry ranges up to 5 Wm^{-2} in some models, twice as large as the current anthropogenic forcing (about 2.5 Wm^{-2}).

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The significance of unphysical albedo asymmetries in the climate models is not yet fully known. However, other model studies suggest that interhemispheric changes in albedo can alter poleward heat fluxes, meridional temperature gradients, storminess, and differences in hemispheric ocean heat storage. The discrepancy between models and observations further raises issues regarding cloud feedback processes and so more generally diminishes confidence in model projections of the future climate.

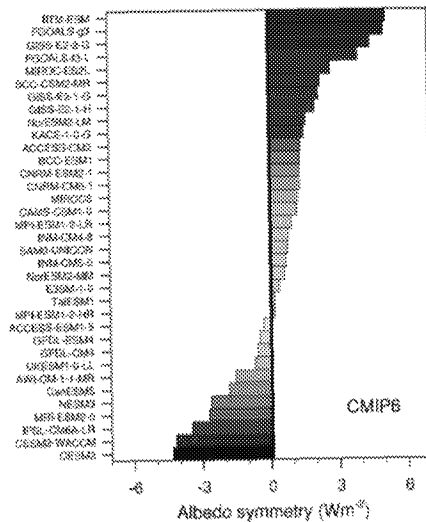


Figure 5.9. Differences in 20-year average reflectivity (albedo) between the Northern and Southern Hemispheres for CMIP6 models used in the most recent IPCC assessment (colored bars). The very small observed difference is indicated by the vertical black line. From Rugenstein and Hakuba (2023).

5.8 U.S. Corn Belt

One of the largest discrepancies between models and observations is in the U.S. Corn Belt, a region of particular importance to global food production. Figure 5.10 shows the warming trends for summertime (June, July, August) for the 12-state Corn Belt (IN, IA, IL, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) warm far too rapidly compared to observations (blue).

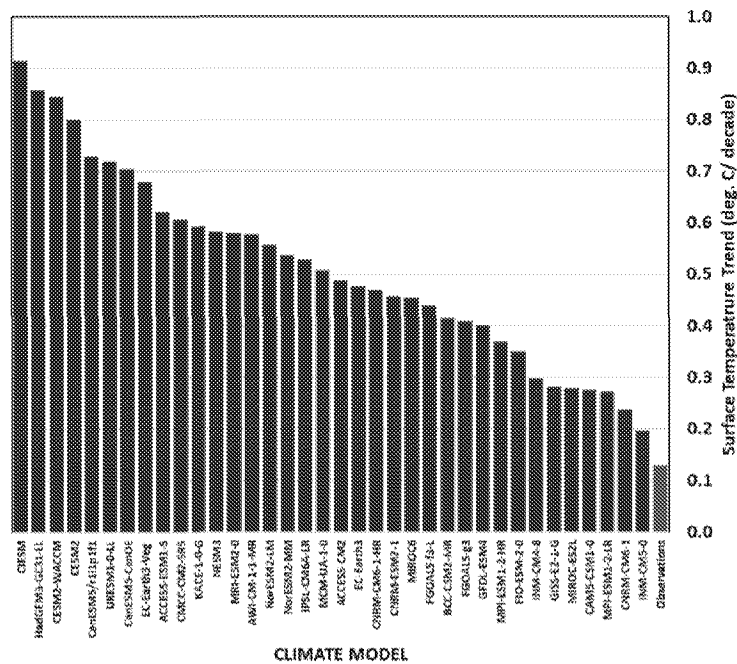


Figure 5.10: Modeled versus observed warming trends in the U.S. Corn Belt, 1973-2022.

As discussed in Chapter 9, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (*e.g.*, Seager *et al.*, 2018).

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The IPCC acknowledges limitations in the accuracy of regional climate model outputs. This example shows that users need to assess model projections carefully on a case-by-case basis since local biases *may* *might* be sufficiently large that the models are simply not fit for purpose. As has recently been noted by two leaders of the modeling community (emphasis added)

... for many key applications that require regional climate model output or for assessing large-scale changes from small scale processes, we believe that **the current generation of models is not fit for purpose.** (Palmer and Stevens 2019)

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades
- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much snow loss, and too much warming in the US Corn Belt.

- The hemispheric albedo difference in individual climate models ranges widely in sign and magnitude compared to observations. The range in W/m^2 is three times larger than the direct anthropogenic forcing of CO_2 .
- The IPCC has acknowledged some of these issues but not others.

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6 EXTREME WEATHER

Chapter Summary

Most types of extreme weather exhibit no statistically significant long-term trends over the available historical record. While there has been an increase in hot days in the U.S. since the 1950s, a point emphasized by the ~~IPCC~~-AR6, numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural ~~variability~~ variability, but long-term increases are not detected. Some increases in extreme precipitation events can be detected in some regions over short intervals but the trends do not persist over long periods and at the regional scale. Wildfires are not more common in the U.S. than they were in the 1980s. Burned area increased from the 1960s to the early 2000's, however it is low compared to the estimated natural baseline level. U.S. wildfire activity is strongly affected by forest management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or high wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., ~~IPCC~~-AR6 Seneviratne *et al.* 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. Climate is about the statistical properties of weather over decades, not single events. Further, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed and thus are absent from the databases used to determine extreme statistics [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This chapter is concerned with detection of trends in extreme weather, while Chapter 8 considers causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed, attribution to human-caused warming does not necessarily follow.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of Long-Term Persistence (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2016). LTP has a formal mathematical definition, but it can be thought of as the presence of natural variations with strong autocorrelations that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records that are short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

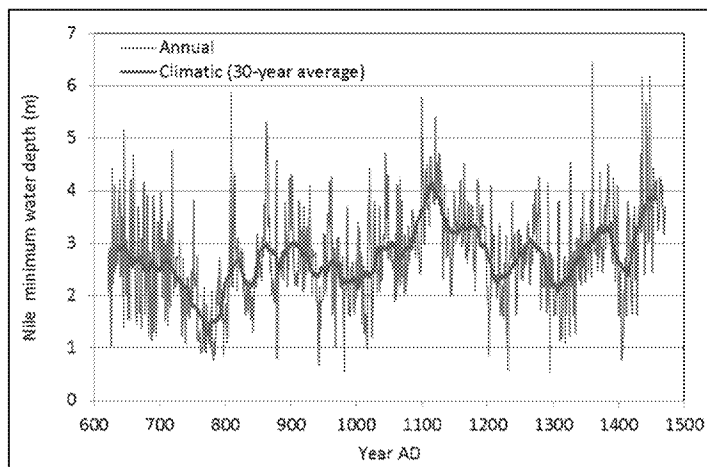


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from Koutsoyiannis (2013)

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown in Figure 6.1.1. The Nile River is fed by precipitation over a 4 million square mile drainage basin, an area equal to about one third of CONUS. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A recurring theme is the wide gap between public perceptions and scientific evidence. It has become routine in media coverage, government and private sector discussions, and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and “climate change.” Yet expert assessments typically have not drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (2012)

AR6: The IPCC Sixth Assessment Report Working Group 1 (2021).

NCA4: The U.S. Climate Science Special Report of the Fourth National Climate Assessment (2017) Volume I.

NCA5: The U.S. Climate Science Special Report of the Fifth National Climate Assessment (2023) Volume I.

In the excerpts, *italics* are in the original whereas **boldface** emphasis has been added.

Additionally we present updated data series from standard government sources to provide up-to-date information through 2024 wherever possible.

6.2 Hurricanes and tropical cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here as a synonym for hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021 p. 1585)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2023 SPM p. 9)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC 2021 p. 1585)

Since 1980, when satellite observations ~~first~~ fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 6.2.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). There is substantial year-to-year and decadal variability, a weak decrease in the number of hurricanes, and a slight but insignificant increase in the number of major hurricanes. These two trends combine to create an overall increase in the proportion of major hurricanes.

Global hurricane statistics are dominated by the Northwest Pacific Ocean, which accounts for ~35 percent of total global hurricanes, whereas the Atlantic accounts for ~15 percent of global hurricanes (Colorado State University, 2025). Data in the Atlantic basin extends further back than in the other ocean basins and is most relevant to U.S. policy makers.

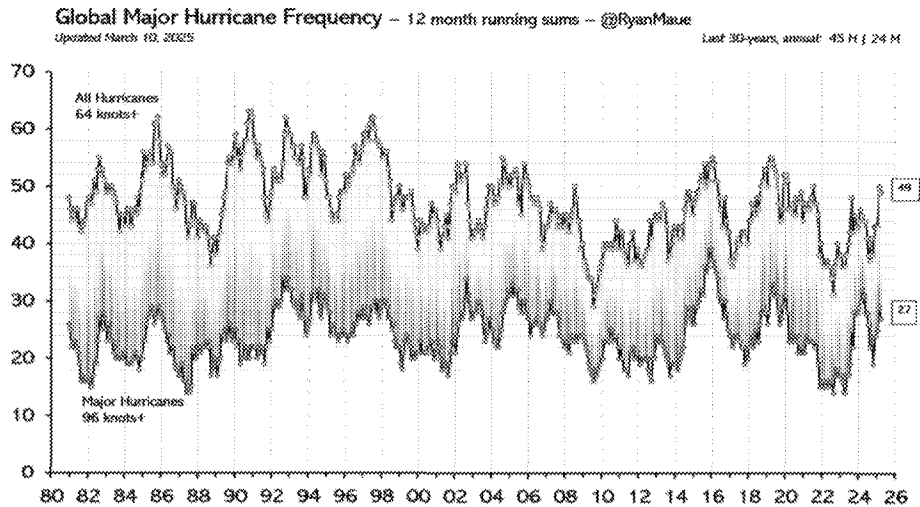


Figure 6.2.1: Global frequency of hurricanes and major hurricanes since 1980.

Figure 6.2.2 shows the frequency of Atlantic hurricanes and major hurricanes (Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (Vecchi and Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 saw exceptionally low activity, with high activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

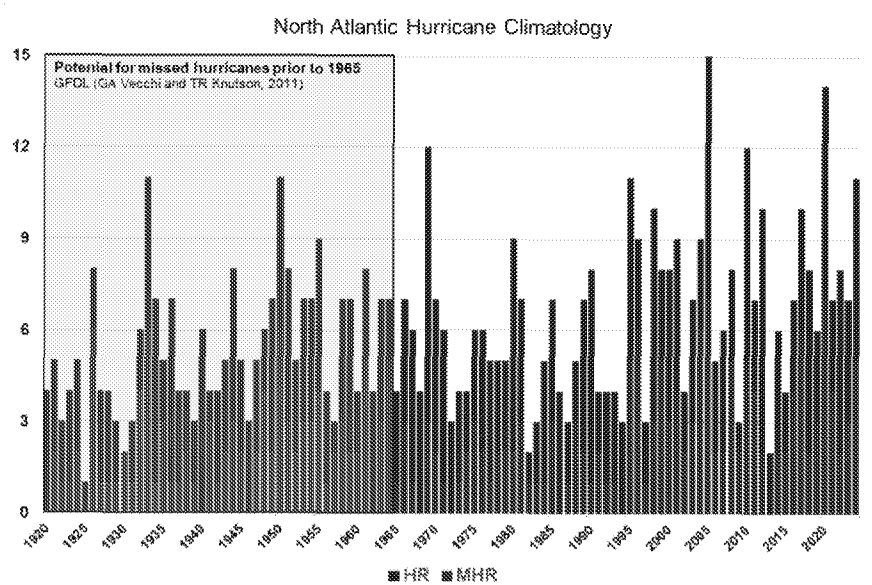


Figure 6.2.2: Atlantic frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source: National Hurricane Center (2024)

Figure 6.2.2 shows that Atlantic hurricanes vary strongly on decadal and multidecadal time scales. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is manifest in basin-wide sea surface temperature and sea level pressure fluctuations connected to large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present, but in its cool phase during 1971-1994. It has its greatest impact on the number of major hurricanes (Category 3+), identified by Goldenberg *et al.* (2001) as associated with above normal SSTs and decreased vertical shear in the AMO warm phase (see also Bell and Chelliah, 2006; Klotzbach *et al.*, 2018).

Klotzbach *et al.* (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.2.3 updates their analysis through 2024. While the largest numbers of landfalling hurricanes are from 2004, 2005 and 2020, there is no statistically significant trend since 1920. Figure 6.2.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, following 2005 there were no major hurricanes striking the U.S. through 2016, the longest such period since 1920.

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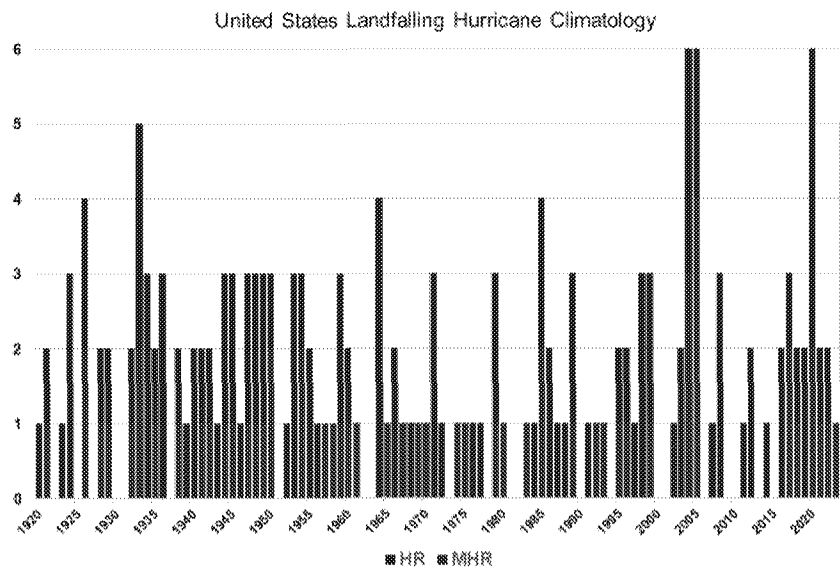


Figure 6.2.3: U.S. landfalling frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source NOAA HRD(a) (2024)

Figure 6.2.3 shows substantial interannual to multidecadal variability in U.S. landfall activity. Klotzbach *et al.* (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini *et al.* (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record is 1886, with 7 hurricane landfalls, when human influences on the climate were much smaller than they are today.

Table 6.2.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation. While it has long been hypothesized that a rising global sea surface temperature would cause an increase in hurricane intensity, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

Table 6.2.1 Strongest hurricanes to make landfall along the U.S. coast. Source (NOAA HRD(b), 2024)

6.3 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. However, the NCA4 noted that heatwave activity in the U.S. reached a peak in the 1930s (Figure 6.3.1).

AR6: It is *virtually certain* that hot extremes (including heatwaves) have become more frequent and more intense across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe (SPM, A3.1)

AR6: In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA. (Chapter 11, p 1550)

NCA4: Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). (pp. 190-191)

NCA4: Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, **heat wave magnitude reached a maximum in the 1930s.** (pp. 190-191)

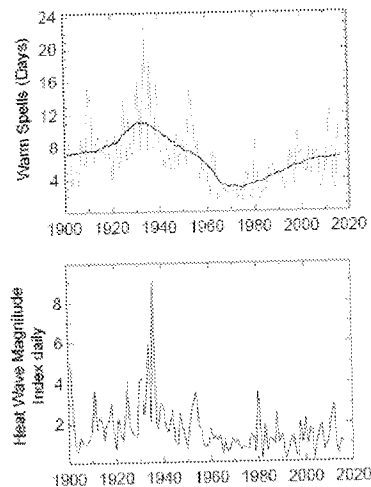


Figure 6.3.1: U.S. Heat waves since 1900. Source: NCA4 Figure 6.4

6.3.1 Temperatures in the U.S. are becoming less extreme

Daily maximum temperatures in the warm season (T max, May-Sep) and daily minimum temperatures in the cold season (T min, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.3.2; Quinlan *et al.* 1987, Karl *et al.* 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves, and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, including unresolved spurious warming due to UHI effects that especially bias T min records, this data set is sufficiently accurate for assessing trends in T max heat extremes.

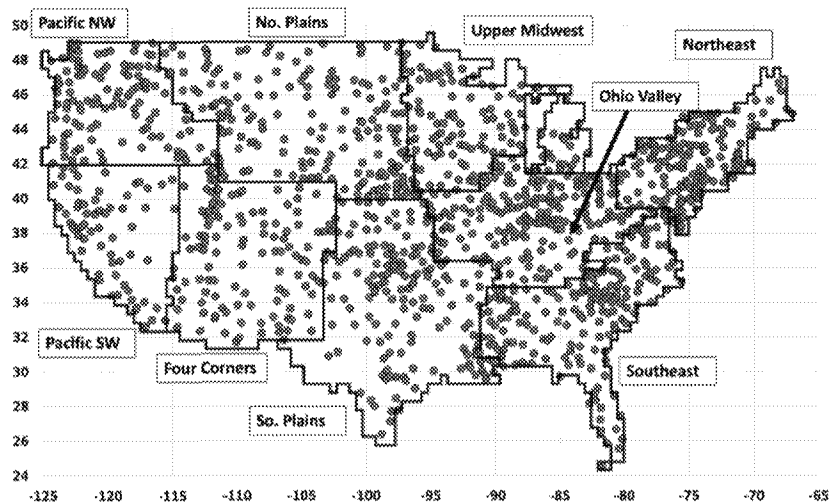


Figure 6.3.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for Tmax would be 1.21 ($=153/126$) per station per year and for Tmin 0.96 ($=122/126$) per station per year.

Figure 6.3.3 shows the observed distribution in time of the occurrence of these extreme events. There is a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60 percent of the Tmax records and 59 percent of the Tmin records occurred in the first half of the period (1899-1961).

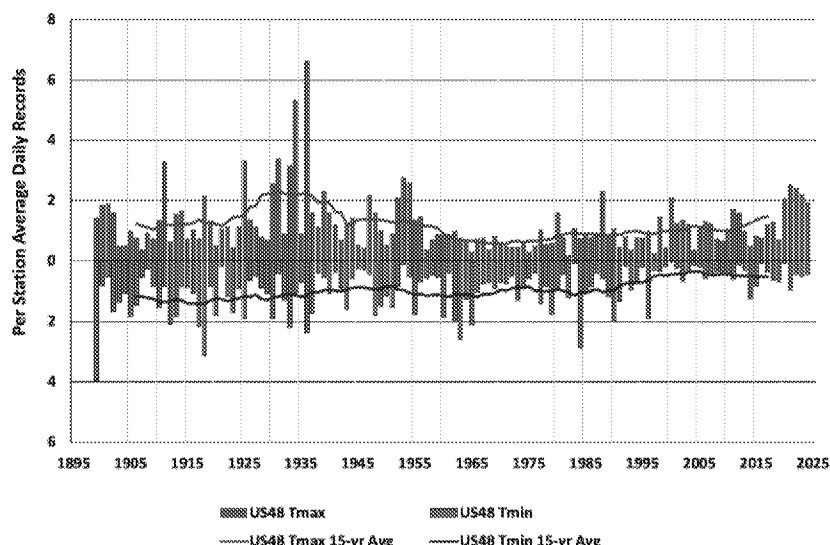


Figure 6.3.3 Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92 percent of observations in the 126-year period since Dec 1898. US48: contiguous U.S. states. Tmax: maximum temperature. Tmin: minimum temperature.

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13 percent of the extreme cold events were measured. In contrast, 25 percent of the extreme Tmax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA4). Combining the two ~~records histories~~, the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.3.4. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.3.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

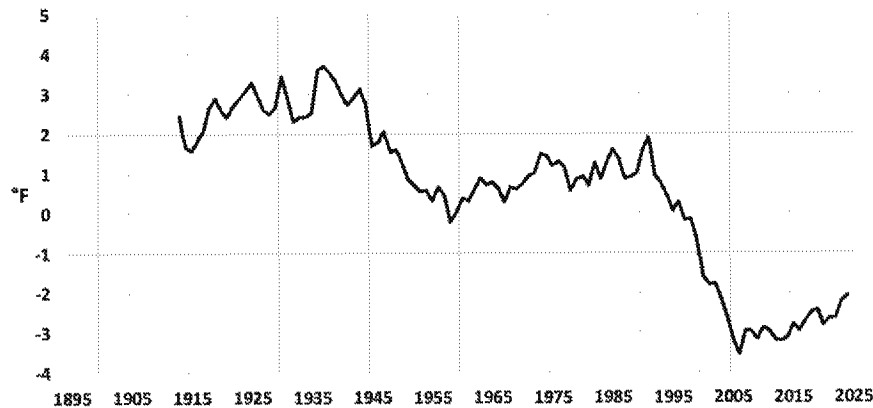


Figure 6.3.4. 15-year trailing average of the difference each year of each station's hottest warm-season Tmax and coldest cold-season Tmin relative to the long-term average. Source: Author analysis of USHCN data.

The average difference for each station between the hottest summer Tmax and coldest winter Tmin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter Tmin, but a decline in summer Tmax is also a factor. The rise in Tmin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; [Section 3.3](#) and [Spencer et al. 2025](#)).

In summary, while temperature extremes are regularly experienced in the U.S. and attract a great deal of media attention, long term records show the U.S. climate has become less extreme over time (milder) when measured by the range between warm season maxima and cold season minima.

6.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent U.S. National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

The western U.S. has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the U.S. since 2018, including a record-shattering event in the Pacific Northwest in 2021.

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F Tmax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F Tmax temperatures, a small change will not have much impact on the results.

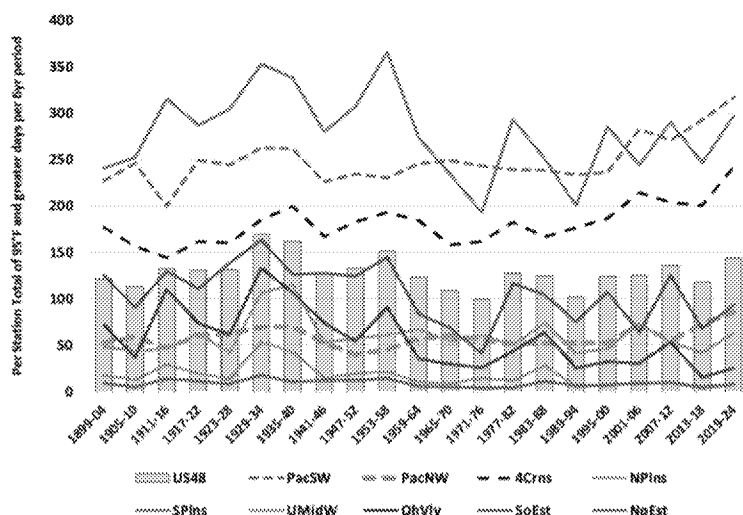


Figure 6.3.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, U.S. 48 (bars) and regions (lines). A 6-year period is used as this evenly divides the 126-year record. US48: contiguous U.S. states. See Figure 6.3.2 for region names. Source: Author analysis of USHCN data.

In the past 126 years, the average CONUS station experienced 129 days exceeding 95°C per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, such threshold analyses must be interpreted with caution. Figure 6.3.5 shows that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 referenced in the NCA5 quote will be examined more closely in Section 8.6.1. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass *et al.* 2024).

The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.

6.3.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile for that day and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA4, except that the reference period here is the entire record 1899-2024 while NCA4 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see Figure 6.3.7 SHOULD IT BE 6.3.6?? and discussion below).

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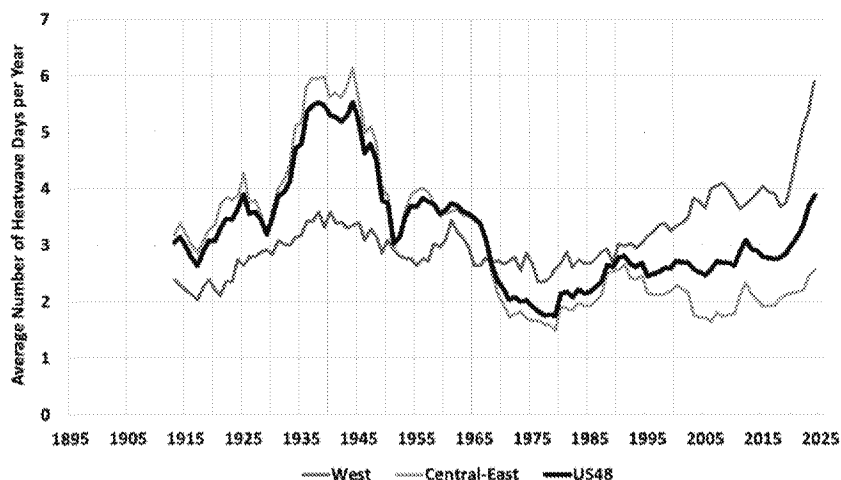


Figure 6.3.6 15-year trailing average of number of heatwave days per year per station in the CONUS (blackline) and two regions: West (red), Central-east (green).

Figure 6.3.6 indicates that there are regional variations in heatwave activity. The excessive heat of the first half of the 20th century occurred primarily in the eastern two-thirds of the nation, while the West has seen a recent increase of heatwave days (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago, consistent with the upper panel of our Figure 6.4.1 taken from NCA4.

This metric varies significantly with region. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

The analysis of heatwaves is an example of why it is important to consider complete datasets and appropriate metrics. The NCA5 directs readers to the website [[HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"](https://www.globalchange.gov/indicators/heat-waves)] (USGCRP 2023) to view a figure showing the number of urban heatwaves by decade from the 1960s, which we reproduce as Figure 6.3.7.

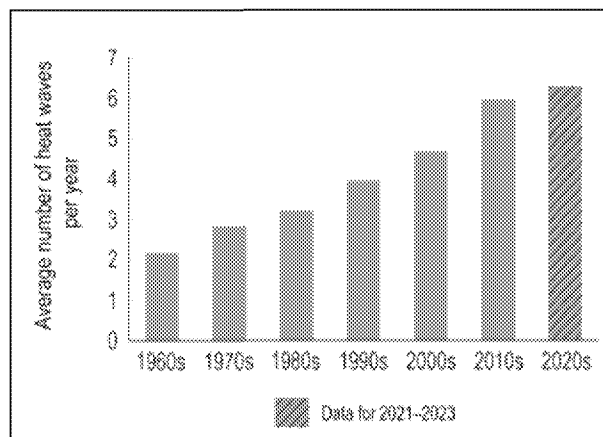


Figure 6.3.7: Average number of urban heatwaves per year for 50 large U.S. metropolitan areas a misleading metric for reasons explained in the text. From [HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"] [LINK BROKEN](https://www.globalchange.gov/indicators/heat-waves)

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The figure shows a monotonic increase in each decade from ~~two~~ occurrences per year in the 1960s to ~~six~~ in the 2020s. The definition of a heatwave used is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the *minimum* apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

Given the unusual heatwave definition and urban focus, these increasing values since 1960 presented in USGCRP (2023) are not informative about long term trends or the influence of GHG emissions for at least two reasons. First, as shown in Figures 6.3.1 and 6.3.6, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. Second, post-1960 urbanization in these cities is a major factor in the rise of T_{min} relative to co-located T_{max} and relative to T_{min} at nearby rural stations. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons; that summer T_{max} (especially in rural areas) is a better metric for detecting changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy *et al.* 2009). For ~~the~~ CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves against the background of urbanization and natural climate variability.

6.4 Extreme precipitation

The IPCC-AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: The frequency and intensity of **heavy precipitation events have increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence). (SPM A3.2)

AR6: In North America, there is robust evidence that the **magnitude and intensity of extreme precipitation has very likely increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018. (Chapter 11, p. 1560)

The U.S. National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme precipitation events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes (Figure 6.3.6).

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast using a trend model with a non-parametric variance estimator robust to the complex autocorrelation properties of precipitation data. When the time series were extended back in time (as far as 1872 in some cases) or ~~when starting started~~ later (1978), there were no significant trends for either region.

These findings have been updated for this report (McKittrick and Christy 2025) with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 27 stations in the Northeast (1888ff from Buffalo NY to Eastport ME). The locations are shown in Figure 6.4.1. The stations were selected based on availability of long-term high-quality records. The regions are each associated with important features of extreme precipitation behavior: the Pacific coast is associated with landfalling atmospheric rivers for which AR6 cites evidence of increasing activity since 1948 with further increases expected as the world warms (AR6 8.3.2.8.2); the NCA report indicates that the Northeast has experienced the greatest increase in extreme events, and the Southeast is also a place noted in the NCAs as having increased extreme events.

The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.

Pacific Coast heavy rainfall events

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- The average precipitation trend is statistically significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov *et al.* 2017, Pan *et al.* 2024). The worst series of such events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862; it dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter *et al.* 2011).

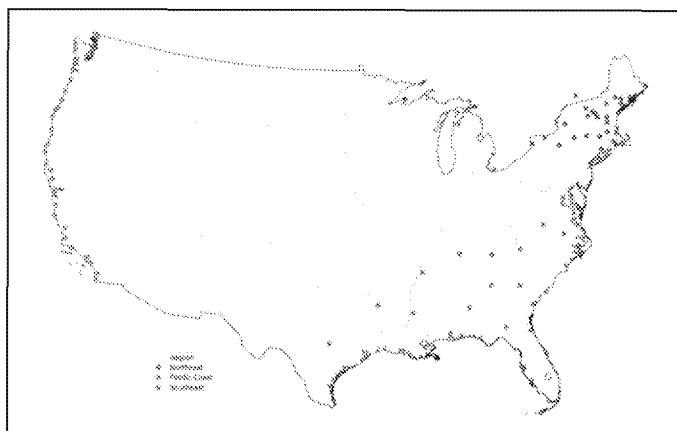


Figure 6.4.1: Locations of precipitation monitoring stations used in this report. Orange: Pacific coast. Blue: Northeast. Green: Southeast. Data from McKittrick and Christy (2025).

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, a 130-year span contains 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year ~~may~~ might have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation, then the total number of these events across all stations should be evenly ~~spread out~~ spread over the years. In Fig. 6.4.2 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of such precipitation metrics, there is no indication of a tendency to become more frequent over time.

Southeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in Mobile AL and Quitman GA but insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA but insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

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Figure 6.4.3 ~~shows the same calculation~~ is analogous to Figure 6.4.2 for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 -- an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

BOX: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent years. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps because of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. And comparing the records of the two charts shows the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme listed in Table 6.2
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter *et al.* (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see Section 8.6). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50 percent determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

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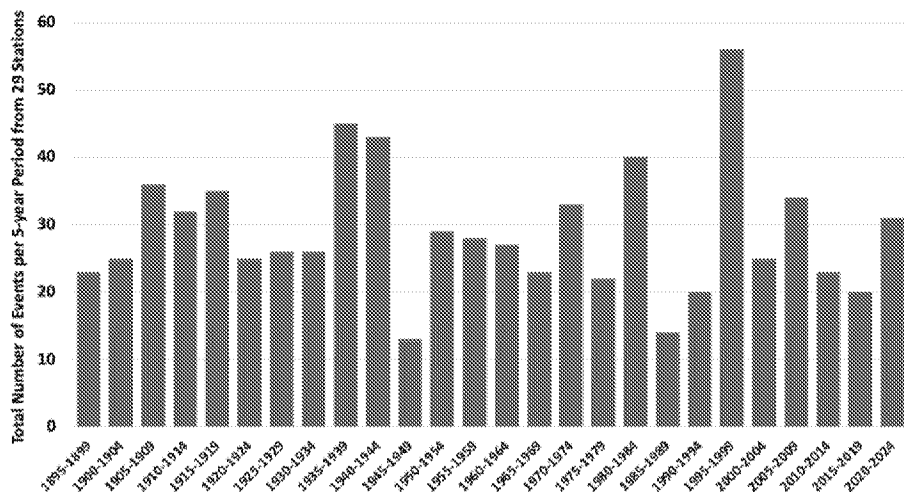


Figure 6.4.2. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

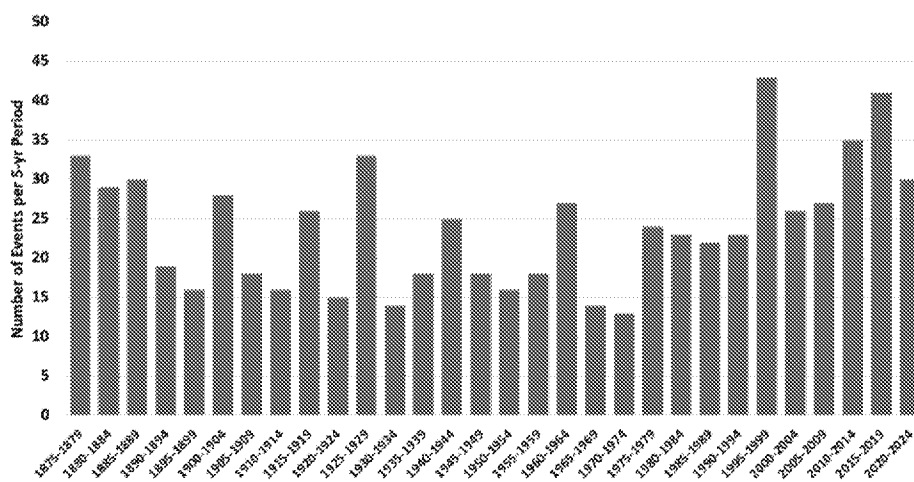


Figure 6.4.3. As in Fig. 6.4.2 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

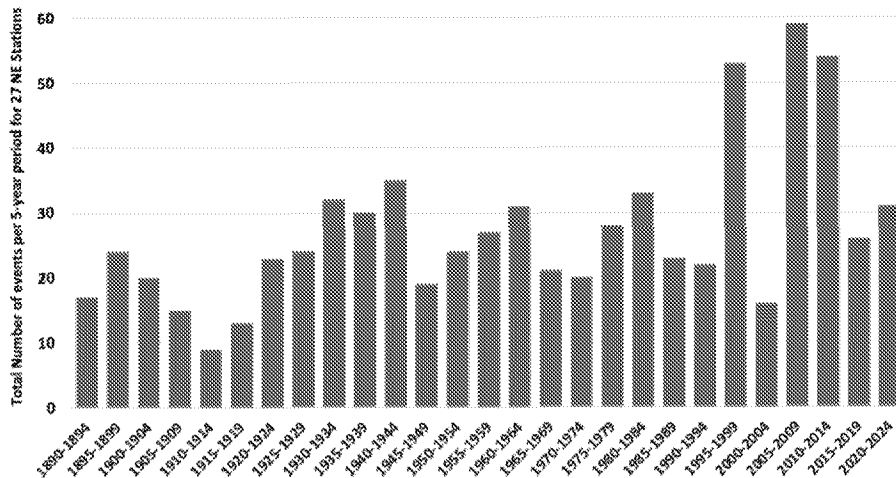


Figure 6.4.4. As in Fig. 6.4.2 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 27 Northeast stations from NY to ME, including Montreal.

Northeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in 12 of 27 locations and also in the regional average.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY, Buffalo NY and Eastport ME but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME, Gardiner ME and Eastport ME but insignificant elsewhere.
- When averaged over all stations in the region, there is no statistically significant trend in either the precipitation variance or maximum

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Fig. 6.4.4 shows the same calculation as Figure 6.4.2 for the last 135 years in 27 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest temporal variations in time. In this region, 77 percent of events occur during June to October and are dominated by incursions of hurricanes, tropical storms, or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it merits a closer examination.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth *et al.* (2019) examined a similar region as in Fig. 6.4.4 that includes PA and NJ and reported significant differences in various precipitation extremes between two 18-year periods, 1979-96 and 1997-2014. That included a 317 percent increase in 24-hr events exceeding 6 inches, while we find a 58 percent increase over the same years. However, Figure 6.4.4 shows that frequency drops sharply after 2014, returning to the long-term average

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in the subsequent 5-year intervals, again illustrating the perils of drawing conclusions from short-term trends in highly variable metrics.

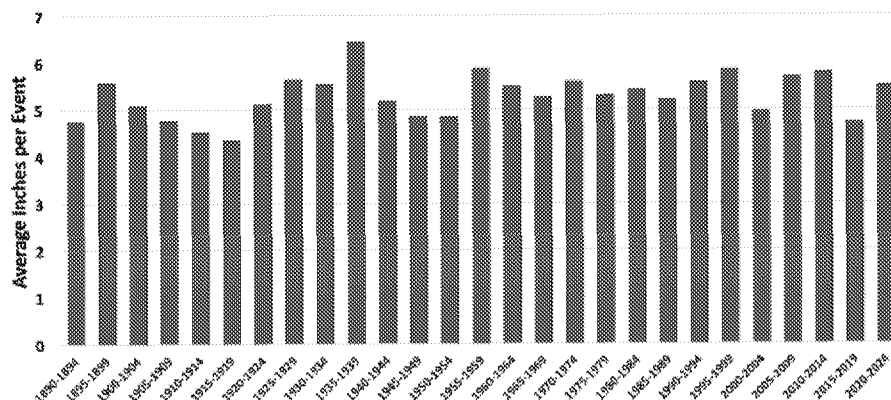


Figure 6.4.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

The high percentage increase in the Howarth *et al.* sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.4.5 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only +0.04 inches/decade. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.4.4 and 6.4.5 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, there was no regional pattern and the change did not persist beyond 2014.

Jong *et al.* (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast U.S. is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: “Was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs?” Jong *et al.* examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.4.5 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact of urban infrastructure on the local weather (e.g., Pielke Sr. *et al.* 2011, Zhang *et al.* 2018, Yang *et al.* 2024). Yang *et al.* state “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.4.5.

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~~INDENT~~ In summary, some U.S. regions show short-duration increases in extreme precipitation events, consistent with natural variability. But analysis of long term, nationwide historical records that considers the autocorrelation properties of precipitation data does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.5 Tornadoes

~~The IPCC~~AR6 assesses tornado trends in the U.S. as follows:

[O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

The monitoring of weak tornadoes has changed over time. The growth of rural populations and the increasing ability to take video with hand-held devices has led to more frequent reports of weak tornadoes that produce minimal damage. In contrast, strong to violent tornadoes have been observed more consistently over time. Note that tornado strength is measured by the damage it produces, not by the visual appearance of the funnel. Limited real-time observational capabilities in earlier decades did not prevent identification because strong to violent tornadoes leave much more damage which will be assessed later even if the tornado itself was not observed. Since statistics began in 1950, there has been a substantial decrease (by about 50%) in the number of strong to violent tornadoes as shown in Fig. 6.5.1a.

To summarize, there is a noticeable downward trend in the number of severe tornadoes in the U.S. since 1950. After 1990 the number of weak tornadoes in the U.S. has remained roughly constant; data before that are incomplete due to limited monitoring.

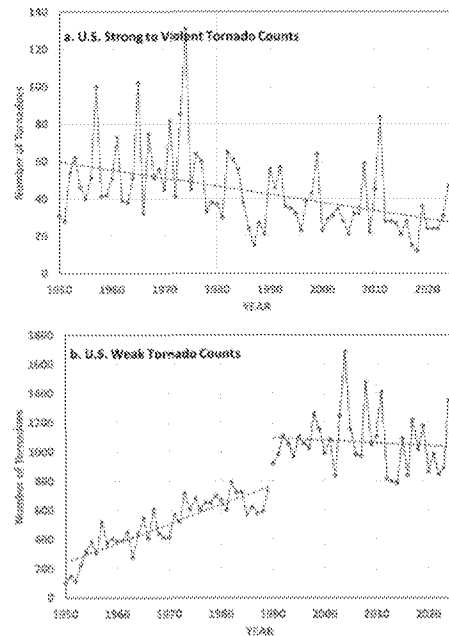


Figure 6.5.1. Annual U.S. tornado counts for (a) strong to violent tornadoes (EF3 to EF5), and (b) weak tornadoes (EF0 to EF2). Based upon NOAA Storms Prediction Center data, available at https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv

6.6 Flooding

Changes in floods were assessed as follows:

AR6: The SREX **assessed low confidence for observed changes in the magnitude or frequency of floods** at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales. (Chapter 11.5)

AR6: [T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*. (Chapter 11.5)

NCA4: Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding

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magnitude **but does not provide robust evidence** that these trends are attributable to human influences (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in Section 6.4 of absence of coherent changes in extreme precipitation.

6.7 Droughts

Assessments of drought trends were as follows.

AR6: Few AR6 regions show observed increases in meteorological drought (Section 11.9, p. 1575),

AR6: Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions. (Chapter 11 Summary)

NCA4: As a consequence of this increased precipitation, **drought statistics over the entire CONUS have declined.** (p. 233)

NCA4: Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence). (p. 231)

SREX: From a paleoclimate perspective, **recent droughts are not unprecedented**, with severe 'megadroughts' reported in the paleoclimatic record for Europe, North America, and Australia. (p. 170)

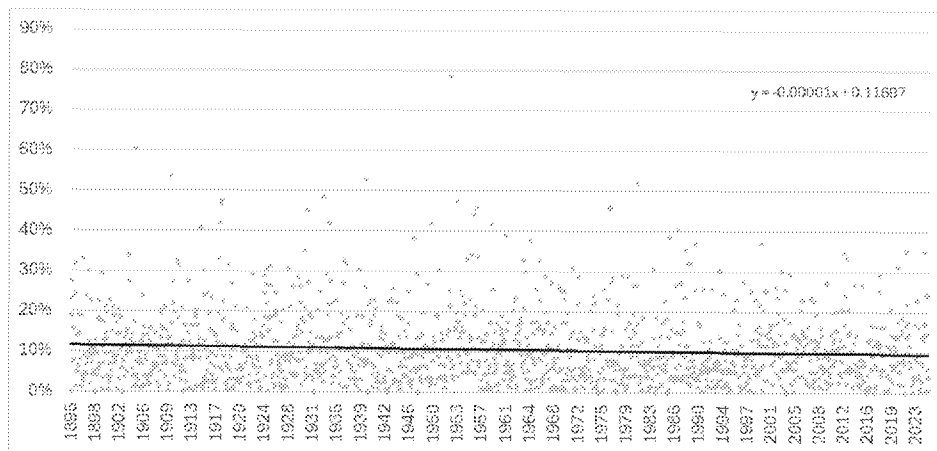


Figure 6.7.1: Monthly percent of US classified as “Very Dry” 1895—2025. Data source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)] least squares trendline added.

As shown in Figure 6.7.1, U.S. long-term data shows an insignificantly declining trend in extreme dryness (-0.001 percent per year)

Kogan *et al.* (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

In summary there is no evidence of increasing drought frequency or intensity in the U.S. or globally over recent decades.

6.8 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.8.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.

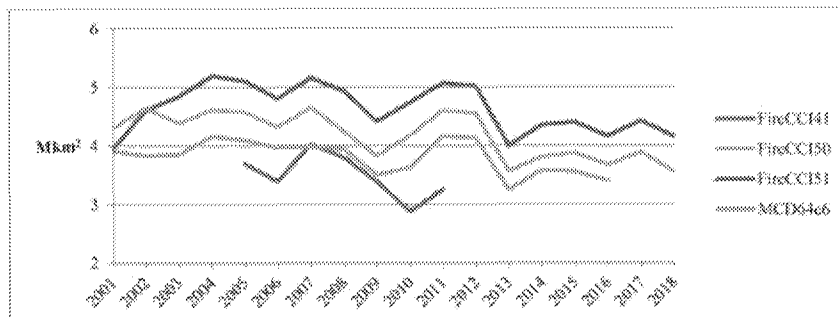


Figure 6.8.1: Global wildfire area 2001-2018. Source: From Lizundia-Loiola *et al.* (2021) Figure 12. The different coloured lines represent data products derived from different satellites and algorithms

Global data show that wildfire coverage is constant or declining on every continent (Samborska and Ritchie, 2024).

Active fire suppression since 1900 makes it difficult to establish a natural baseline for wildfire activity in the U.S. Paleoclimatic evidence indicates that past activity was much higher than today. Marlon *et al.* (2012) used sedimentary charcoal layers to reconstruct fire history of western U.S. for the past 1400 years and also fit a model to predict fire activity as a function of climatic conditions. Their results are summarized in Figure 6.8.2 below (from Figure 2 in their paper). There has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century, it was less than what would have been observed in previous centuries based on the climatic conditions. Parks *et al.* (2025) likewise find

that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

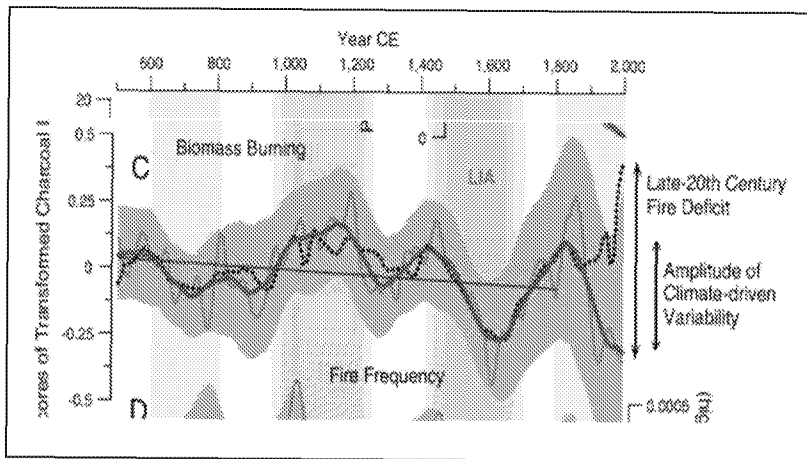


Figure 6.8.2 Fire frequency and fire deficit in the US. The red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based climatic conditions model. Source: Marlon *et al.* (2012) Figure 2.

U.S. data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.8.3. The NIFC has removed the pre-1960 data from its current website on the grounds that measurement methods changed after 1960 making the comparison unreliable. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life, including humans. Science has confirmed the overall benefit and necessity of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile U.S. forest fire remains the 1910 Big Blowup fire in the U.S. west, which destroyed over three million acres and eliminated entire towns like Taft, MT (Apple, 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal of defeating all forest fires (Forest History Society, 2022). This led to the “10 am rule” in 1935 requiring that all fires spotted on any day had to be controlled by 10 am the following day (National Forest Foundation, 2022).

While defeating all fires seemed a noble goal, questions began to arise as to whether this behavior “followed the science” (U.S. Forest Service, 2022). Over time the U.S. Forest Service has begun to rethink its goals, recognizing that new approaches such as prescribed burns, fuel elimination, and controlled wildfires are more appropriate (Sommer, 2016). Recent research is validating this approach and recognizing

that more frequent smaller fires likely result in healthier forests, water ecosystems and biodiversity (Stephens *et al.*, 2021).

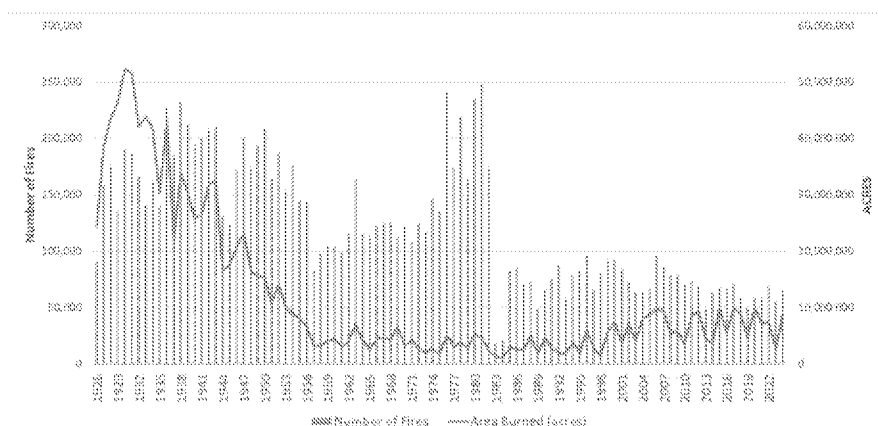


Figure 6.8.3: U.S. wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Center data [[HYPERLINK "https://www.nifc.gov/fire-information/statistics/wildfires"](https://www.nifc.gov/fire-information/statistics/wildfires)]. Pre-2017 webarchive.org (n.d.).

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7 CHANGES IN SEA LEVEL

Chapter Summary

Since 1900, global average sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also with ocean circulation patterns. The largest sea level ~~rise-increases~~ along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions - each of these locations is associated with substantial local land sinking (subsidence) unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothetical ice sheet instabilities. In evaluating the IPCCAR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the ~~sea level rise has already occurred by time has elapsed by 2025, with sea level rising, and at a lower rate than predicted.~~ U.S. tide gauge measurements ~~shown herein reveal no obvious acceleration beyond the historical average rate of sea level rise.~~ ~~TRIED TO REMOVE THE AMBIGUITY IN THE PREVIOUS SENTENCE~~

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7.1 Global sea level rise

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCCAR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (Fox-Kemper *et al.*, 2021). The rate of global sea level rise is estimated to be 0.12 inches/year, (about the height of two stacked pennies) (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters in 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860, well before most anthropogenic greenhouse gas emissions.

7.2 U.S. sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 7.1 shows that in Canada and Alaska (and also northern Washington), sea level is decreasing, owing to uplift from glacial rebound. Most of the Pacific coast tide gauges show low rates of sea level rise, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

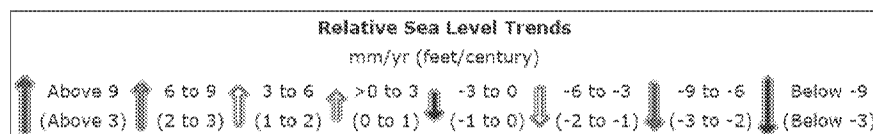


Figure 7.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/strends/>). For reference, 3 mm = 0.12 in.

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. The latter, which varies from place to place, is best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (Wöppelmann and Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (*e.g.* for urban development purposes) and subsurface extraction of groundwater or hydrocarbons.

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Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; Letetrel *et al.*, 2015; Karegar *et al.*, 2016). The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

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Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

Table 7.1 Absolute sea level rise (inches/year) consisting of Relative Sea Level Rise (RSLR) plus Vertical Land Motion (VLM)

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.2). As shown in Table 7.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (Shirzaei and Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, are caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

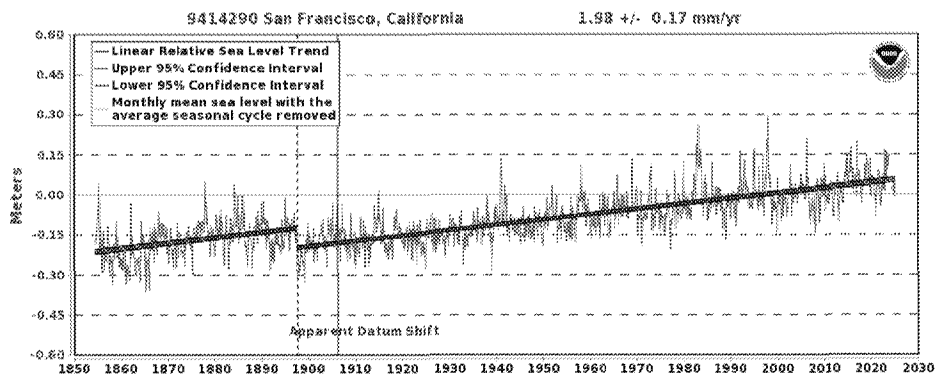


Figure 7.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/strends/strends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (Kasmarek and Ramage 2017), which caused compaction of the aquifer

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sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

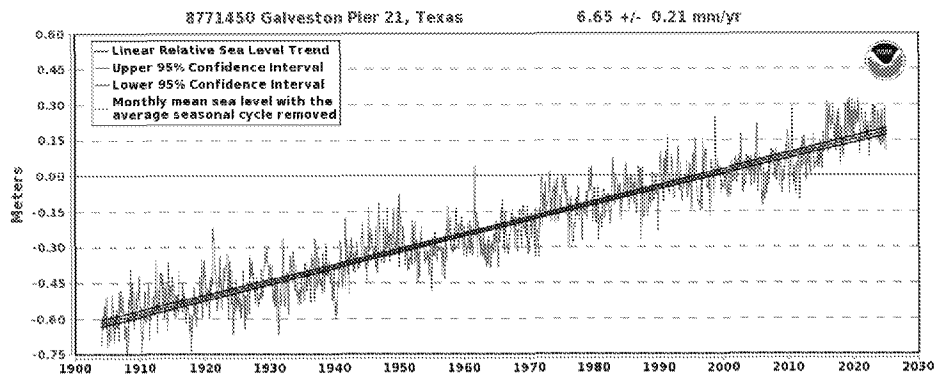


Figure 7.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 7.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 7.1 gives the absolute sea level rise as +0.08 inches/year.

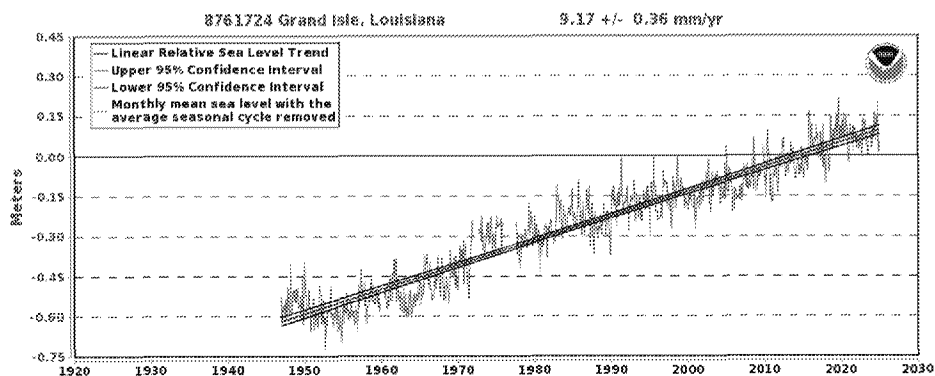


Figure 7.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi River being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi's suspended sediment load by ~50 percent (Maloney 2018). A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (Neinhuis *et al.* 2017), associated with groundwater and resource withdrawal. As the city's elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans' problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (The Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 7.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55 percent of the measured relative sea level rise.

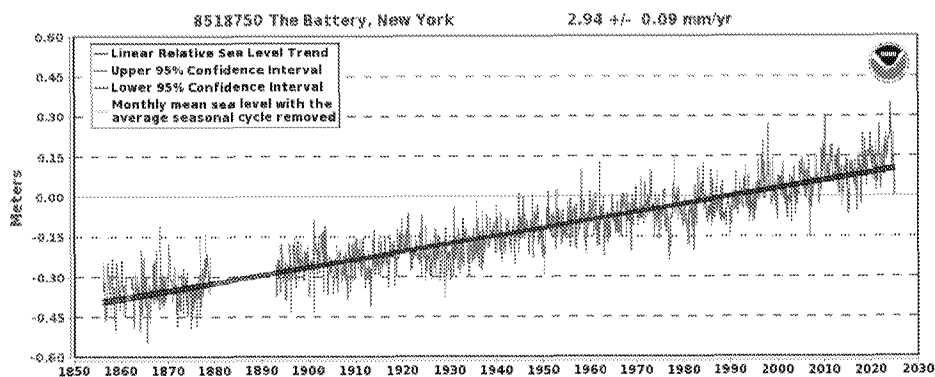


Figure 7.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

7.3 Projected sea level rise

The concern over sea level rise is not about the roughly eights inches of global rise since 1900. Rather, it is about projections of *accelerated* rise based upon simulations of a warming climate through the 21st century.

The IPCC AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (Fox-Kemper *et al.*, 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (Fox-Kemper *et al.*, 2021). There is deep uncertainty surrounding projections of sea level rise to 2100 owing to uncertainties in ice sheet instabilities, particularly for the higher emissions scenarios.

In February 2022, NOAA issued its projections of sea level rise for various sites along the U.S. coast (Sweet *et al.*, 2022). They claim that by 2050, the sea will have risen one foot at The Battery in Manhattan (relative to 2020). A one-foot rise in thirty years would be more than twice the current rate and about three times the average rate over the past century. In that historical context, NOAA's projection is remarkable—as shown in Figure 7.6, it would require a dramatic acceleration beyond anything observed since the early 20th century. But even more noteworthy is that Sweet *et al.* (2022) say this rise is “locked in”—it will happen no matter what future emissions are. We should know in a decade or so whether that prediction has legs.

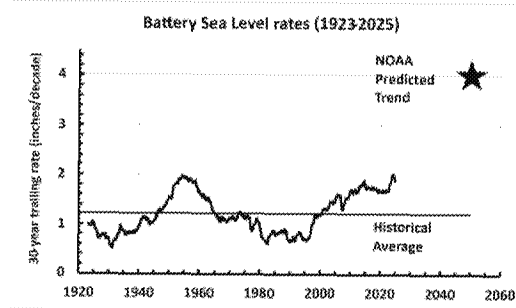


Figure 7.6 Rate of sea level rise at the Battery in Manhattan. Shown is the historical thirty-year trailing trend, together with the allegedly “locked in” NOAA predicted trend for 2050. Historical data: NOAA Tides and Current.

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8 UNCERTAINTIES IN CLIMATE CHANGE ATTRIBUTION

Chapter summary

“Attribution” refers to identifying the cause of some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and in aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (*e.g.* event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

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8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.

Attribution: Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.

Both detection and attribution rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, (such as GHG emissions), versus natural factors, (like volcanic eruptions), contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially those for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. AR4 Working Group I (Hegerl *et al.*, 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

AR5 Working Group II (Cramer *et al.*, 2014) makes the following statement:

Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

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8.2 Attribution methods

The IPCC employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key IPCC attribution methods.

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model is weighted to try to minimize the influence of random noise and the estimation method is chosen to account for climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (*e.g.* heat waves or droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings might have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: **Most of the observed increase** in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations. (IPCC 2007)

AR5: It is *extremely likely* that **more than half of the observed increase** in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human- induced contribution to warming is similar to the observed warming over this period. (IPCC 2013)

AR6: The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that **well-mixed GHGs were the main driver** of tropospheric warming since 1979. (IPCC 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began ~~rapidly~~ increasing *rapidly*. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99 percent of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850–1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – ~~AR6~~ AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from ~~the~~ AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 5, while this chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 Natural climate variability

~~IPCC~~ AR6 states that natural external drivers since 1850–1900 have changed global surface temperature by –0.1°C to +0.1°C, and internal variability has changed it by –0.2°C to +0.2°C – on average having essentially no net impact on the warming since 1850–1900. As discussed below, this minimal contribution of natural variability has been disputed by several publications that question the magnitudes of solar variability and internal variability from large-scale ocean circulations.

Solar variability

~~IPCC~~ AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was very small (0.05 W/m², Myrhe *et al.*, 2014). ~~IPCC~~ AR6 acknowledges substantially higher values and a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half

of the twentieth century increased by 0.7–2.7 W/m², a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact of solar forcing on the climate was still assessed to be small compared to anthropogenic forcing. However, the impact of solar variations on the climate is uncertain and subject to substantial ~~debate~~ (Lockwood, 2012; Connolly *et al.*, 2021) – something that is not evident from the IPCC assessment reports.

The variations of TSI over time remains a challenging problem. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibits non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, ~~disagreeing that disagree~~ as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used to calibrate proxy models, ~~that infer whereby~~ past solar variations ~~are inferred~~ from sunspots and cosmogenic isotope measurements (Velasco Herrera *et al.*, 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos *et al.*, 2023; Solanki *et al.*, 2004; Usoskin *et al.*, 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

This uncertainty causes some reconstructions of TSI from 1750 to have low variability (implying a very low impact of solar variations on global mean surface temperature) whereas datasets with high TSI variability can explain more than 70 percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). The choice of TSI satellite record used in an analysis can therefore substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, either amplify TSI forcing or are independent of TSI forcing. Scafetta *et al.* (2023) suggests that ~80 percent of solar influence on climate ~~may-might~~ stem from non-TSI mechanisms. There are numerous candidate processes, including solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Such solar indirect effects are not included in climate models, although indirect methods of estimating their impacts suggest they are significant. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models have too little amplitude compared to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov *et al.* 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (*e.g.* CO₂ forcing). With

most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

AR5: Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.

AR6: Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (*high confidence*).

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: "The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021)." This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out owing to differences in phasing, effectively cancelling the role of natural internal variability in the attribution process.

The time series of global surface temperature anomalies since 1850 (Figure 8.1) shows irregular variations of significant amplitude against the background of an overall warming trend and, after 1976, a pronounced difference in trends between the Northern Hemisphere and the Southern Hemisphere. The period between 1905-1945 shows a strong trend of warming. The following ~~about 30~~ years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

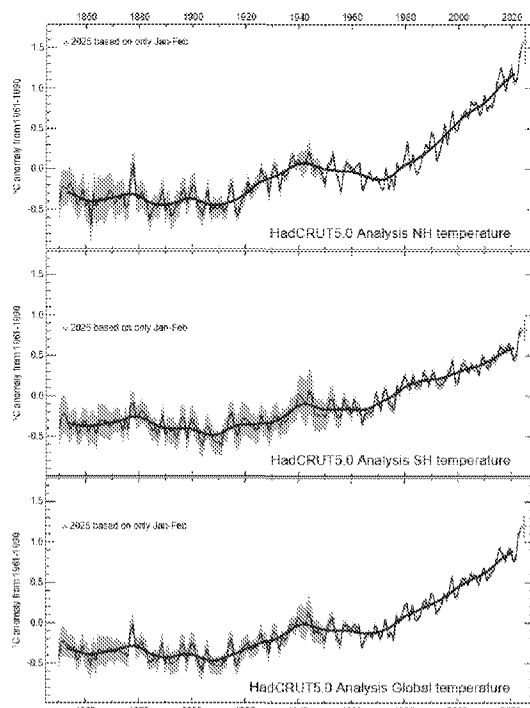


Figure 8.1 Global average surface temperature anomalies 1850—2025. Top: Northern hemisphere. Middle: Southern hemisphere. Bottom: Global average. Source: UK Hadley Centre [[HYPERLINK "https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf"](https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf)]

The causes of the early 20th century warming are discussed by Hegerl *et al.* (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941, implying that CO₂ had little impact. Volcanic activity during this period was very low, and solar forcing is uncertain. Yet Hegerl *et al.* (2017) somehow inferred that 40–54 percent of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman *et al.* (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular Mode was positive, with a strengthened Amundsen–Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid-century was particularly pronounced in the Arctic. Bokuchava and Semenov (2021) find that these variations were most likely caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural radiative forcing related to the reduced volcanic activity and variations of solar activity, as well as growing greenhouse gases concentrations. Tokinaga *et al.* (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic

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warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale circulations over the Northern Hemisphere; these same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation and Atlantic Multidecadal Oscillation; cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson *et al.* (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns, including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean *et al.*, 2009; Tung and Zhou, 2013; Chylek *et al.*, 2016; Scafetta, 2021).

8.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or “fingerprints”) associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of “signals”, which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares (TLS). The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the research literature. While it has been widely used and prominently featured by the IPCC since 2001, there is very little literature examining the statistical properties of the results it generates. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

A series of papers by McKittrick (McKittrick 2021, 2022, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that practices adopted from econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2021) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen *et al.* (2023) confirmed this analysis, although they argued that the method could yield valid results under very stringent assumptions. McKittrick (2022) and (2023) raised a further concern that climate scientists—virtually alone among

scientific disciplines—have used ~~an estimation method called Total Least Squares (TLS)~~ to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unstable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions that easily arise in optimal fingerprinting, TLS estimates have a large positive bias. Thus, any study that used TLS for optimal fingerprinting without verifying its applicability in the specific data context has likely overstated the attribution.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics that are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which is consistent with the estimate by Lewis (2023) using a different estimation method and multiple independent data sets.

While these analyses do not falsify ~~results stemming from~~ the IPCC optimal fingerprinting method, they do challenge the basis on which they were believed to be correct.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. These have the advantage of not depending on assumptions about the accuracy of climate models, but the disadvantage that they depend on difficult-to-test assumptions about the data generating process underlying climate and forcing data. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades *et al.*, 2016, Balcombe *et al.*, 2019, Dagsvik *et al.*, 2020, Razzak, 2022, Dagsvik and Moen, 2023).

“Granger causality” modeling is a tool for determining directions of influence in data series that move together. It is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable, we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error in Al Gore’s documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson *et al.* (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data, the coherence in the series is primarily due to the influence of temperature on CO₂ levels, not the feedback of CO₂ levels on temperature.

In summary, the primary statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend

on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Declining planetary albedo and recent record warmth

A sharp recent increase in global average temperatures has raised the question of short-term drivers of climate. One such candidate is the fraction of absorbed solar radiation which has also increased abruptly in recent years. The question is whether the change is an internal feedback to warming caused by greenhouse gases, or whether something else increased the fraction of absorbed radiation which then caused the recent warming.

The planetary albedo is the fraction of incoming solar radiation that is reflected back into space rather than being absorbed by the planet. Highly reflective surfaces like cloud tops and snow and ice are most important in this regard. The Earth's albedo is approximately 30 percent, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed by the planet to be then re-radiated as heat. Hence, other things being equal, a decline in planetary albedo is associated with a warming of the Earth.

Arguably the most striking change in the Earth's climate system during the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure 8.2 shows the planetary albedo variations since 2000, when there are good satellite observations. The 0.5 percent reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in absorbed solar ~~energy-power~~ averaged over the planet (Hansen and Karecha, 2025). For comparison, the IPCC estimate of forcing from the increase in atmospheric CO₂ compared to preindustrial times is approximately 2.2 W/m² (Figure 3.1.2).

Looking back prior to 2000 with less adequate data, Goessling *et al.* (2025) assessed that ~~the~~ planetary albedo was relatively low around the 1940's and 50's, before rising industrial aerosol precursor emissions increased ~~the~~ albedo until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum ~~may~~ ~~might~~ have been the lowest since at least 1940.

Changes in surface characteristics cannot explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5 percent since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England *et al.*, 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that "There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability." (Summary for Policymakers, A.1.5)
- Northern hemispheric annual snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer. [HYPERLINK "<http://climate.rutgers.edu/snowcover/>"] ~~and Section 5.6~~
- Global greening (Chapter 2) is contributing to the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo ~~increase~~ ~~decrease~~ associated with increasing forested area.

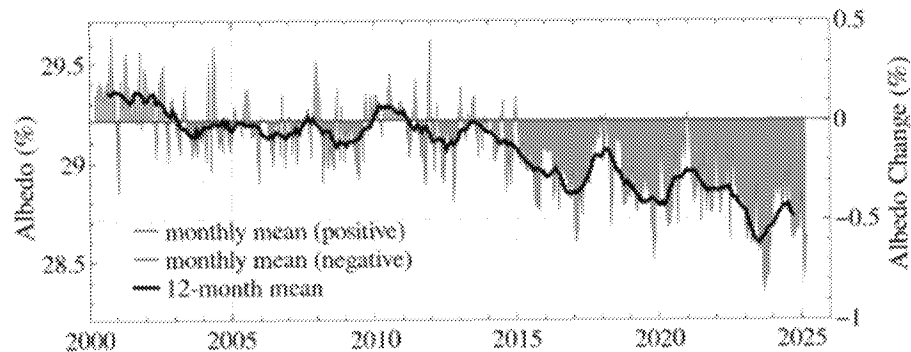


Figure 8.2. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor of three on average, primarily due to cloud masking (Loeb *et al.* 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally. This leaves the most likely explanation for the sharp albedo decline as changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (*e.g.* dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall might ~~be producing~~ produce less dust. For anthropogenic aerosols, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog *et al.*, 2024; Yuan *et al.*, 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

Changes in clouds are the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb *et al.*, 2024; Goessling *et al.* 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb *et al.* found that decreases in low- and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the Northern hemisphere, whereas in the Southern hemisphere the decrease in planetary albedo is primarily due to decreases in mid-level clouds across all latitude zones. Goessling *et al.* (2024) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

The issue then becomes the causes of the change in cloud cover. Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability

- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

~~It is not easy to justify the existence of a new positive low cloud feedback that began emerging in 2015, is not easy to justify.~~ However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was one of the strongest El Niño events on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams *et al.*, 2017; Arthun *et al.* 2021).
- The Pacific Decadal Oscillation positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Niño Southern Oscillation (ENSO) have a significant global signal and strong regional signals, especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Goessling *et al.* (2024) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz *et al.*, 2025; Kuchar *et al.*, 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of the Hunga Tonga eruption on the planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the recent trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and for the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

8.5 Attribution of climate impact drivers

The IPCC (Ranasinghe *et al.* 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest in assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold,” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC

also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first ~~three~~ columns of Table 12.12 in Ranasinghe *et al.* (2021, p. 1856), reproduced here as Table 8.1, summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Out of the 33 weather impact categories ~~listed~~, an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Further, two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, ~~or drought~~.

~~Other columns 2 and 3~~ of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We have omitted these columns for several reasons. First, because they refer to whether climate models project detectable signals in the observations, which is a very different question than our concern here; whether a signal has been detected in historical data. Second, as we discuss in Chapter 4, the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Third, the ensemble of detailed models is acknowledged (Palmer and Stevens 2019) to be “not fit for purpose” in describing regional changes and “unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided.” (Nissan *et al.*, 2019). Even with these caveats, we note that the omitted columns in AR6 Table 12.12 show most weather impacts are not expected to exhibit an anthropogenic signal ~~through the end of this century~~.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	4
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fog weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	11
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwave	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease

Medium confidence of decrease

Low confidence in direction of change

Medium confidence of increase

High confidence of increase

Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

As discussed in Chapter 6 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that, again contrary to popular belief, ~~it is not currently possible to attribute attributes of changes in most extreme weather types to human influences. It is not currently possible.~~ Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

8.6 Extreme event attribution (EEA)

Examining the IPCC's treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between its chapters. Chapter 11 of WG1 states (Seneviratne *et al.*, 2021):

Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.

By contrast, as noted in Section 8.5, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of particular extreme weather events. The most prominent effort is World Weather Attribution (WWA; worldweatherattribution.org), an international research initiative for extreme event attribution that purports to analyze how climate change influences the likelihood and intensity of extreme weather events. Their approach is to use large ensembles of regional climate models to compare an event in today's climate with one in a counterfactual pre-industrial climate without human influences.

WWA has a prominent public presence in linking extreme weather to climate change, with its press releases attracting considerable attention in public and policy discussions. However, the WWA's extensive promotion of non-peer-reviewed findings, ~~its funding~~ its open admission to shaping analyses to serve litigation, and its methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of their conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to influence climate science and media narratives. Technical criticisms of the approach include a lack of a formal detection process; an implicit assumption that 100 percent of the post-industrial warming is caused by greenhouse gases; and a failure to adequately account for internal climate variability.